Characterization, Prediction, and Mitigation of Code Help Events at Massachusetts General Hospital

by

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Submitted to the MIT Sloan School of Management and the Civil and Environmental Engineering Department
in partial fulfillment of the requirements for the degrees of

Master of Business Administration

and

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Abstract

This thesis suggests a method to characterize congestion alarms triggered by the Emergency Department (ED) at Massachusetts General Hospital, attempts to predict the incidence of these alarms using logistic regression, and proposes operational recommendations for the mitigation of congestion events termed *Code Help.* In order to characterize *Code Help* alarms, we begin by identifying a set of relevant operational features that allow us to describe them objectively and proceed to clustering *Code Help* observations using k-means. We regress these features on binary variables indicating *Code Help* incidence to predict, at 7AM in the morning, whether or not *Code Help* will occur on a given day. Based on this analysis, we suggest a set of recommendations to operationalize a more effective response to *Code Help.* Our characterization uncovers three main classes of *Code Help*: those exhibiting a high level of ED arrivals in the hour preceding the alarm with a relatively low operational utilization of inpatient beds, those exhibiting a low level of ED arrivals in the hour preceding the alarm with a relatively high operational utilization of inpatient beds, and those exhibiting high arrivals and utilization. The logistic regression identifies two statistically significant predictive features: ED Census at 7 AM and the Number of Boarders in the ED at 7 AM, scaled against same time of day and day-of-week observations. Moreover, we identify discharge orders and outpatient pharmacy orders as early discharge indicators that can be used to prioritize Medicine patients in terms of their readiness to be discharged when *Code Help* is called.

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Chapter 1

Introduction

This project aims to objectively characterize congestion events known as *Code Help* at the Massachusetts General Hospital Emergency Department using operational data features, predict them in advance, and recommend effective mitigation measures to them. The project has been conducted by the MGH-MIT collaboration under the guidance of the MGH Capacity Task Force. Background information on these organizations is provided in the following sub-sections.

1.1 Massachusetts General Hospital

Massachusetts General Hospital (MGH), founded in 1811, is a teaching hospital for Harvard Medical School, and almost all its physicians are on the medical school faculty [1]. It is a 1,305-bed medical center that offers cutting edge diagnostic and therapeutic care across a plethora of specialties and subspecialties of medicine and surgery. The hospital also holds concurrent Level 1 verification for adult and pediatric trauma and burn care [2]. Massachusetts General Hospital has been ranked among the top five hospital in the United States by U.S. News & World Report since the rankings began [3] and was recognized by The Leapfrog Group for quality and safety with an "A" grade in 2018 [2]. As the top ranked hospital in Massachusetts [3], MGH sees approximately 50,000 inpatient visits, 110,000 emergency room visits, and 1.5 million outpatient visits every year [4]. Massachusetts General Hospital and Brigham and Women's

Hospital founded Partners Healthcare in 1994. Today, Partners consists of primary care and specialty physicians, community hospitals, a managed care organization, specialty facilities, community health centers, and other health-related entities, in addition to the two founding academic medical centers. Together these providers offer a continuum of coordinated, high-quality care [5].

1.2 The MIT-MGH Collaboration

The MIT-MGH Collaboration is a longstanding research partnership between Massachusetts General Hospital and the Sloan School of Management at the Massachusetts Institute of Technology, focusing on advancing the operational effectiveness of the hospital using Operations Research tools. The MIT-MGH team comprises MIT faculty, MGH leadership, students from the Operations Research Center and Leader for Global Operations (LGO) Program, and graduate and undergraduate MIT students from other programs.The research presented in this thesis has been conducted under this Collaboration.

1.3 The Capacity Task Force

In order to combat heightening capacity problems, MGH launched the Capacity Task Force in January of 2016: a team of hospital administrators, providers, data analysts, and members of the MGH-MIT Collaboration joining forces to identify solutions to immediate and longer term capacity challenges. The task force was divided into three subgroups – the first focusing on avoidable ED and inpatient care, the second on preventable readmissions, and the third on delays related to patient placement and bed allocation [6]. The project described in this document resides within the first work group – Capacity Task Force 1 – facilitated by the Executive Director of Emergency Services and Emergency Preparedness, Mr. Robert Seger. Capacity Task Force 1 held weekly meetings, hosting providers and administrators from other departments such as Perioperative Services and Healthcare Systems Engineering, Admitting, General

Medicine, Surgery, and Billing to get their view on the capacity problem tackled in this document.

1.4 Project Motivation

1.4.1 Emergency Department Visit Volume

Massachusetts General Hospital is a Level I Trauma Center, a Level I Pediatric Trauma Center, and a Level I Burn Center. Since the day it was founded, MGH has been serving patients requiring emergency care. The Emergency Department at Massachusetts General Hospital comprises seven care areas: Acute, Urgent, Fast-Track, Evaluation, Clinical Decision Unit (CDU), Pediatrics, and Acute Psychiatric Service (APS). Patients are triaged by the greeter nurse into one of the areas according to the type and level of care that they require based the symptoms they present to the ED with. As of the time of writing of this thesis, the MGH ED had a total of 66 beds, out of which 46 are monitored beds[1] [7]. As is shown in Figure 1-1, the number of visits to the MGH ED has been climbing over the past decade, from an average of 215 visits per day in FY06[2] to a staggering 303 visits per day in FY16. The MGH ED is expected to start seeing an average of 340 visits per day in FY20.

[1] Bedside monitors keep track of different vital signs, helping ED providers quickly identify changes and complication in a patient's condition

[2] Fiscal years at MGH begin on October 1st and end on September 30th.

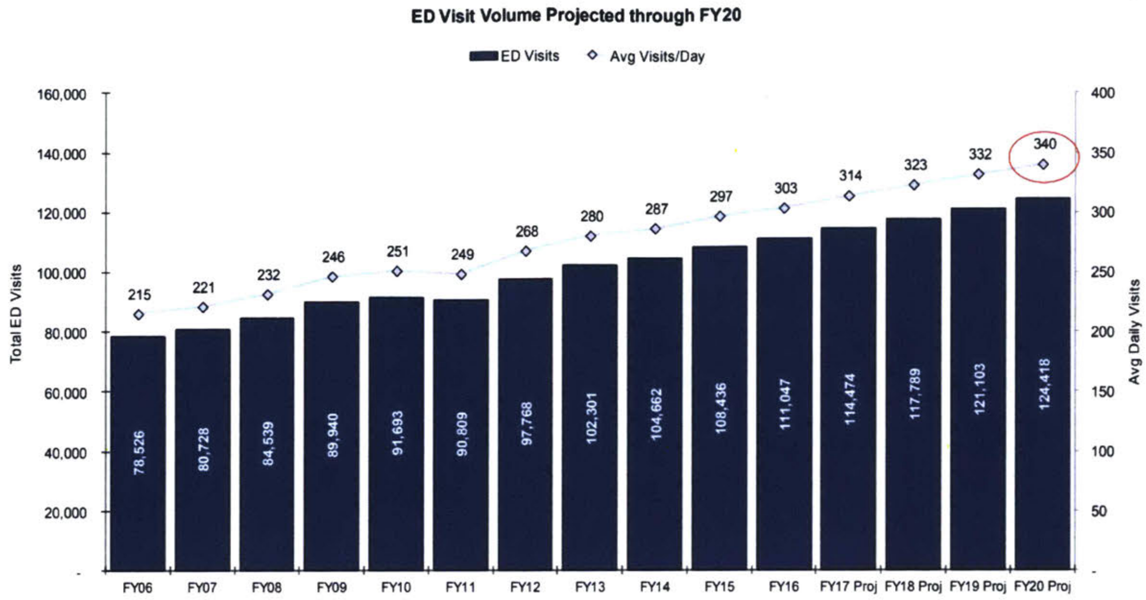

Figure 1-1: MGH ED Visit Volume.

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

EMTALA is a federal statute that was enacted by Congress in 1986, requiring hospitals to screen, stabilize, and treat all patients seeking care regardless of their ability to pay or their insurance status. EMTALA applies to facilities that accept Medicare or Medicare reimbursements from the US government, which means that all hospitals in the United States – excluding hospitals operated by the military or Shriners International – have an obligation to comply with it [6]. Since Massachusetts General Hospital is a participating hospital, the MGH ED is not allowed to turn away any patient without treatment, regardless of the condition they present with.

1.4.3 Banning Ambulance Diversion

Ambulance diversion is the practice of temporarily closing a facility, typically an emergency department, to incoming ambulances. This practice has been used since the 1990s to relieve emergency department overcrowding. On January 1, 2009, Massachusetts successfully banned this practice except in cases in cases of internal hospital disasters that render the emergency department unusable. One predicted consequence of prohibiting ambulance diversion was severe crowding of overwhelmed emergency departments forced to accept all those who sought care, as mandated by EMTALA [8].

1.4.4 The Code Help Capacity Protocol

As a result of the banning of ambulance diversion, and in an effort to mitigate ED crowding in hospitals across the state, the Massachusetts Department of Public Health (DPH) requested that all hospitals submit a *Code Help* plan: a policy that would be enacted to move all admitted patients out of the ED within 30 minutes when its licensed capacity is reached or exceeded. This policy is to be activated when the ED is no longer able to care for its existing patient population or accept new patients into a licensed treatment space. The *Code Help* policy is required to state the chain of command for activation when certain trigger thresholds are reached. If *Code Help* implementation does not relieve the ED from the burden of admitted patients in a defined time (e.g., 1-2 hours), or if the severity of the situation warrants, then the hospital is asked to activate the appropriate disaster plan to create additional inpatient capacity[9]. At the MGH ED, the *Code Help* capacity protocol was designed to relieve congestion as it occurs in the Acute and Urgent care areas that host the most acutely sick patients of the ED population. *Approaching Code* Help gets activated automatically when all eighteen Acute beds are full with two hallway slots occupied and all twenty-two Urgent beds are full with one hallway slot occupied; the response team is paged[3]. If two more beds become occupied in Urgent and another two beds receive patients in Acute, the Acute Attending, Resource Nurse, and Charge Coordinator huddle and decide whether or not to call *Code Help*.

[3]Appendix A contains details on recipients of the page.

1.4.5 *Code Help* Implementation Challenges

The implementation of the *Code Help* protocol at the MGH ED brings with it a number of operational challenges.

First, despite there being specific objective thresholds on patient census in Acute and Urgent, it does not seem that they are followed consistently. For example, on certain occasions, ED decision-makers will decide to activate *Code Help* even if the objective thresholds are not reached for reasons related to patient safety. On other occasions, they might refrain from activating *Code Help* because they expect that they will be able to move a certain number of patients out of the ED in a relatively short timeframe, thereby relieving congestion. Based on this, the *Code Help* definition itself starts to seem narrow, as it relies on census metrics internal to a section of the ED and does not consider the overall state of the hospital in terms of capacity and patient flow. Contextual operational data is not currently available in real-time to *Code Help* decision-makers.

Second, *Code Help* response measures are currently ineffective in relieving congestion and almost never achieve their goal of moving admitted patients out of the ED within the required time frame of 30 minutes. Alarms are becoming more frequent over the years, generating alarm fatigue and confusion among responders. ED administrators and providers will admit that reasons behind the prevalence and intensification of these alarms are unclear.

Finally, it is very difficult to create additional inpatient capacity during *Code Help* events when no centralized real-time information exists about inpatients who are approaching discharge.

More details about the *Code Help* response protocol can be found in Chapter 3.

1.5 Project Methodology

The principal aim of our work is to address the *Code Help* implementation challenges directly by providing insight into the drivers behind of *Code Help* activation and attempting to form an understanding of the mental model of *Code Help* decision-makers. To that end, we cluster *Code Help* events using k-means and generate an objective characterization of their underlying causes.

Moreover, we tackle the challenge of the currently ineffective response to *Code Help* by providing a reliable prediction – using ED operational features – of whether or not *Code Help* is likely to occur on a specific day at 7 AM in the morning using logistic regression with L-1 and L-2 regularization. Additionally, we identify early indicators of discharge for inpatients so that those nearing discharge may be accelerated through the process when bed capacity is scarce.

In an effort to reduce unnecessary alarms, we also propose a design for a dashboard to be used during *Code Help* huddles. This dashboard contains real-time operational features that provide ED staff with information about the broader state of hospital capacity so that they are able to make a more informed decision during the *Code Help* huddle.

1.6 Main Hypotheses

The main hypotheses that drive this work are:

1. Not all *Code Help* events are equal – *Code Help* events might occur for different reasons and these reasons are identifiable through unsupervised clustering techniques used on clinical and operational data. The main drivers of *Code Help* are a high number of ED arrivals and a busy hospital;

2. There exists enough evidence in the clinical and operational data gathered by MGH at 7 AM in the morning that would allow the prediction, using supervised learning techniques, of *Code Help* incidence at any point on a specific day; and

3. There exists clinical and operational data currently gathered in real-time at MGH that would allow the identification of inpatients that are in the process of being discharged.

1.7 Key Results

The project establishes three main insights. First, that there are three main classes of *Code Help*:

1. Those that are driven by a surge in upstream patient arrivals into the ED;
2. Those that are driven by a high operational capacity utilization[4] of inpatient beds on Medicine floors[5]; and
3. Those that are driven by both a surge in upstream patient arrivals and high operational capacity utilization of inpatient beds on Medicine floors

Downstream congestion seems to be a key factor that influences the incidence of *Code Help*. In fact, 46% of occurrences exhibited a high operational capacity utilization of Medicine beds and a low rate of ED arrivals in the last hour prior to the alarm. Moreover, 42% of all observations recorded both a high operational capacity utilization of Medicine beds and a high rate of ED arrivals in the last hour prior to the alarm. Only 12% of all observations recorded a high rate of ED arrivals and a low bed operational capacity utilization of Medicine beds.

The second insight established is that *Code Help* events can be predicted with reasonable accuracy at 7 AM on a given day by examining clinical and operational data from the hospital. In fact, a logistic regression model with L-2 regularization (Ridge) achieved a median AUROC[6] of 0.72, and in some permutations of the dataset, reached values of 0.85.

Finally, it was found that patient Discharge Orders allow a median lead time of 1 hour until discharge on *Bigelow 11* and a median lead time of 3.5 hours until discharge on *Ellison 13*. For the population of patients that are prescribed Outpatient

[4]The ratio of the number of beds that are utilized by a patient to the total number beds that are available for use (i.e. excluding beds that are blocked for maintenance or infection control)

[5]MGH Blake 11 Psych; MGH Blake 13 Ob; MGH Ellison 10 Stp Dwn; MGH Ellison 11 Card Int; MGH Ellison 16 Med; MGH Ellison 17 Pedi; MGH Ellison 18 Pedi; MGH Ellison 19 Thor Med; MGH Bigelow 9 RACU Med; MGH Bigelow 9 Med; MGH Bigelow 11 Med; MGH Lunder 7 Neuro; MGH Lunder 8 Neuro; MGH Lunder 9 Oncology; MGH Lunder 10 Oncolo Medicine; MGH White 11 Medicine; MGH Phillips 21 Gyn; MGH White 8 Medicine; MGH White 9 Medicine; MGH Ellison 12 Med.

[6]Area Under the Received Operating Characteristic Curve

Pharmacy Orders during their stay (17.58% of total patient population), using Outpatient Pharmacy Orders will allow a better lead time than Discharge Orders 29.65% of the time. Further, if MGH were able to bring down the time between the filing of a discharge order and patient discharge on all floors that are currently in the upper 50th percentile to the value of the median, it would be able to free up 0.2% of its total Medicine bed capacity.

1.8 Thesis Organization

Following this introduction, Chapter 2 continues with a literature review summarizing research on Emergency Department overcrowding causes and solutions. Chapter 3 then provides a detailed description of the ED's physical organization and patient flow, as well as supplemental background information. Chapters 4, 5, 6, and 7 summarize the methodologies and key findings stemming from the project's analyses of the characterization of *Code Help* events, the identification of early indicators of discharge, *Code Help* prediction, and the recommendation of mitigation measures, respectively. Finally, Chapter 8 concludes the thesis with a summary of conclusions and suggestions for future research.

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Chapter 2

Literature Review

2.1 Emergency Department (ED) Overcrowding

ED overcrowding arises when there is no capacity left to meet the needs of the next patient requiring emergency care in a timely manner. The problem of ED overcrowding first came to public attention in 1987 and the first statewide conference on overcrowding was held in New York City, involving the New York (NY) chapter of the American College of Emergency Physicians (ACEP), New York Emergency Medical Services (EMS), the NY State Department of Health, and state legislators. Since that day, the subject of ED overcrowding has been studied in depth by many research groups around the world. ED congestion causes problems for patients, hospital staff, and providers equally, including longer than usual wait times, increased level of ambulance diversion, increased length-of-stay, and increased medical errors which could lead to an increased mortality rate among ED patients [10].

2.1.1 Causes of Emergency Department (ED) Overcrowding

Several reasons have been hypothesized to explain ED overcrowding: (i) sub-optimal utilization of ED beds and resources, (ii) competition for inpatient beds between ED population and patients admitted for elective surgery procedures, and (iii) staffing issues and inefficiencies in ED processes[10, 11]. Some have blamed the poor and under-insured for utilizing excessive ED capacity, however, studies have established that the status of a patient's health insurance does not correlate with the frequency of their ED visits [12]. In fact, a study of all ED visits to Ontario hospitals from April 2003 to March 2003 concluded that there was little evidence of low-acuity patients affecting wait times or overcrowding in any event [13]. More recently, several studies have found that inpatient boarding[1] shows a strong relationship with ED overcrowding [10, 14], indicating that hospital congestion could be the root cause of the problem. Another issue that has been proven to lead to ED congestion, especially in urban hospitals, is the front-loading of the surgical schedule towards the beginning of the week [15]. Surgery patients that come in early in the week will compete for hospital capacity with ED patients, potentially leading to ED congestion [10]. Lastly, it has been shown that decreased nursing hours have correlated with and increased ED length-of-stay for discharged patients; it follows that insufficient nursing staffing levels in the ED can also lead to overcrowding [11].

2.1.2 Solutions to Emergency Department (ED) Overcrowding

Numerous studies have considered potential solutions to mitigate the overcrowding problem that are internal to the ED and consist mostly of operational improvements. For example, one study suggested performing patient registration at the bedside rather than in the front of the ED in order to decrease triage-to-room times for patients[16]. A few studies have explored increasing the number of beds in the ED and concluded that this measure is largely ineffective and leads to an increase in the number of boarders [17, 18]. A study from Johns Hopkins suggested that adding a hospitalist that would focus on bed management decreased throughput time for admissions by 100 minutes, and decreased ambulance diversion[2][19]. This hospitalist would coordinate with ED caretakers, Admitting administrators, and inpatient care

[1]Boarders are patients who remain in the emergency department after they have been admitted or placed into observation status at the facility, but have not been transferred to an inpatient or observation unit.

[2]This practice is illegal in the state of Massachusetts. See section 1.4.3 for more details.

teams in order to streamline patient admission from the ED into an inpatient floor. Placing a provider in triage and flexing ED staffing levels to match patient throughput has also been studied[20, 21].

Other solutions that have been examined focused on factors external to the ED. First, it has been shown that the smoothing of elective surgeries and early discharge improve boarding in the ED [22]. In the same vein, increasing weekend discharges has been shown to increase capacity as the week begins, thereby decreasing ED congestion [10]. Full capacity protocols have been examined as a solution to the ED overcrowding problem. A first study by Viccellio, et al. concluded that placing patients on inpatient units in hallways is a safe practice [23]. In another survey study, Garson, et al., demonstrated a strong patient preference for being on the inpatient service rather than boarding in the ED [24].

2.1.3 Consequences of Emergency Department (ED) Overcrowding

Over the past few years, a large volume of research has been conducted on the consequences of overcrowding in the ED. These include delayed care for sick patients, increased total length of stay in hospital leading to decreased access, increased walk-out rates, decreased quality of care and increase in medical errors, increased mortality rates, and increase in ambulance diversions. The Commonwealth of Massachusetts' Department of Public Health (DPH) is the first state regulatory body to mandate specific, hospital action plans to reduce ED boarding via its *Code Help* policy. A number of regulatory and state agencies support efforts to reduce ED boarding by permitting inpatient floor boarding or mandating reporting of ED flow data, but none except for the Massachusetts DPH appear to have mandated specific, hospital action plans with pre-defined triggers [25].

2.2 Previous Work at the MGH ED

Previous work by Hoffmann [6] established that secondary admissions were being referred to MGH while it was not clear that they could not receive a similar level of care at other institutions. A scorecard was developed to assist MGH in understanding the facilities whose patients consume the most hospital capacity on a relative basis. Machine learning models and a scoring method have been developed to identify avoidable admissions. These efforts are central to reducing ED congestion because transfers are growing at a swift pace, increasing arrivals disproportionately relative to other patient populations[6]. Our work determines whether ED congestion is mostly due to a spike in patient arrivals into the ED or if it is a byproduct of high capacity utilization of inpatient beds. Further, we predict ED congestion ahead of time and recommend fit-for-purpose mitigation measures.

Chapter 3

Data Sources, Patient Flow in the ED Environment, and *Code Help* Protocol

This chapter provides a necessary background for the work detailed in this thesis. First, it describes the data sources for the analyses that we conducted and whose details results we will present in later chapters. In addition, it describes the ED environment, focusing on patient flow, in order to give the reader the context and background required to fully understand our analyses. Finally, we thoroughly detail the *Code Help* policy of the MGH ED and present an analysis on the frequency of occurrence and time distribution of *Code Help* events.

3.1 Data Sources: *Epic* and *D4Q*

3.1.1 Data Sources

In April of 2016, MGH adopted *Epic Systems*, an integrated electronic medical record system. *Epic* is a healthcare software system that tracks patient healthcare episodes, such as outpatient visits, medical history, hospital encounters, and general patient information. It is used across Partners HealthCare, so any visit to a Partners hospital or outpatient facility is documented electronically. Many of the data elements are updated in real time, and nearly all relevant patient data is electronically stored [26]. *ADT* tables live in the *Epic* environment and document patient flow information such as arrival timestamps, transfer timestamps, and discharge timestamps. Particularly, the *Encounter* table is used in our work to determine timestamps for patient discharges and transfers into another medical facility. This information is central to the analyses that we carried because it allows us to examine patient flow characteristics such as arrival rates or census numbers around *Code Help* events and contrast it with normal values.

The information in the *ADT* tables also allow us to calculate the number of utilized beds on Medicine floors and, from that information, infer their operational capacity utilization. *Epic's Enterprise Data Warehouse (EDW)* allows us access to clinical information such as the discharge timestamp from the *PatientEncounterMGH* table and the timing of filing of a discharge order or a discharge summary from the *ProcedureMGH* table. *MedicationMGH* and *Pharmacy* tables allow us to determine the time of filing of a pharmacy order to an outpatient pharmacy.

D4Q is a database that contains information about the patient experience and flow for ED patients. In this work, we utilize the *PatientEncounter* tables from the *D4Q* database in order to determine arrival and departure timestamps, for each patient encounter, which in turn allows us to determine ED census. From *D4Q*, we also utilize the *EDCareArea* table which allows us to determine features like boarding status[1], arrival time, and departure time, current ED pod that we use to determine operational features that we can slice and examine by pod. The *EDStatus* table allows us to determine whether the ED is in *ED Open*, *Approaching Code Help*, *Code Help*, or *Capacity Disaster*.

[1]Whether or not patient is considered a boarder.

3.1.2 Datasets

Table 3.1: Timeline of Data Analysis

Table	Database	Key Features	Timeline
PatientEncounter	*D4Q*	ED Census	05/01/2016 - 07/31/2017
EDCareArea	*D4Q*	ED Census, Number of Boarders, Average Boarding Time	05/01/2016 - 02/28/2018
EDStatus	*D4Q*	Time of Activation of Alarms	05/01/2016 - 12/31/2017
Ecounter	*Epic.ADT*	Inpatient Discharges, ED Discharges, ED Transfers-out	04/01/2016 - 09/30/2017

3.2 Patient Flow

3.2.1 Patient Flow Through the MGH ED

As can be seen from 3-1, the MGH ED treated around 110,000 patient visits in FY16, 24.5% of whom (about 27,000 patients) were later admitted to hospital floors. These 27,000 patient admissions through the MGH ED make up about a substantial 54% of all inpatient admissions that occurred that fiscal year.

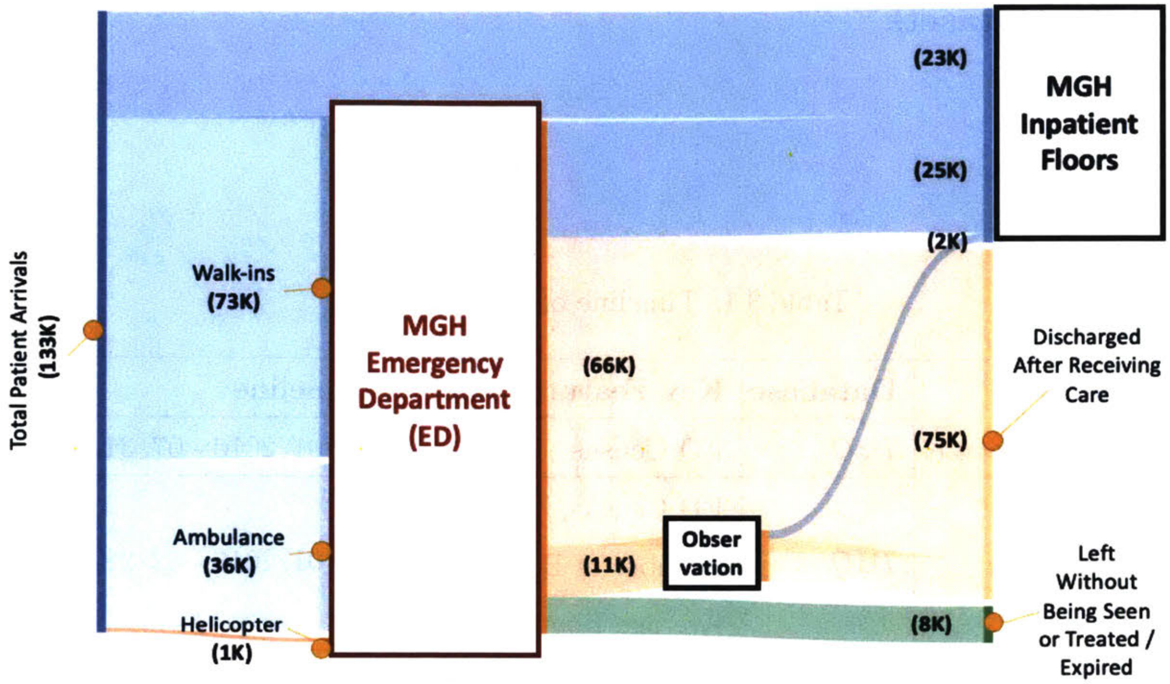

Figure 3-1: Patient Flow through the MGH ED (FY16).

Patients arrive to the ED through multiple modes including walk-ins, ambulance transport, and helicopter transport. About 7% of ED patients leave without being seen or treated, or expire in the ED. Close to 60% of ED patients are discharged directly after receiving care, and 10% are sent to an ED Observation Room where they are monitored overnight and later admitted as inpatients or discharged after receiving care depending on the progression of their symptoms and care path.

3.2.2 Patient Flow Within the MGH ED

In general, patients arriving to the ED are routed through two initial steps: (i) Reception, and (ii) Triage. During Triage, it is determined to which of the seven department's treatment areas they should proceed: (i) Acute; (ii) Urgent; (iii) Fast Track; (iv) the Clinical Decision Unit (CDU); (v) the Acute Psychiatric Service (APS); (vi) the Pediatric Emergency Department (PED); and (vii) Evaluation. 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 3-2 describes the flow of patients within the department [6].

The reception area is reserved for walk-ins since patients entering via ambulance and helicopters have their own reserved entryways. When a patient walks in, they are met by a clinical greeter, or Greeter Nurse, who upon examining them, will guide them to a treatment, screening, or waiting room. Five screening bays located next to the ED's reception area serve as the ED's triage zone. Triage is a brief examination during which a patient's vitals are measured and a chief complaint is determined. Ambulance and helicopter crews can conduct triage via radio. Other than patients who require medical attention, all patients will proceed from Triage to waiting in the Pre-Eval area outside Evaluation that includes nine evaluation rooms. The Eval team will conduct a thorough examination of the patient, who can be either directed to one of the six other treatment areas in the ED, treated and released to return home, or sent to an external medical facility in some situations. The Acute area is reserved for the care of the ED's most seriously ill or injured patients, where providers work on stabilizing patients and admitting them to the most appropriate inpatient service within MGH. Patients who are severely ill but are not in immediate danger of loss of life or limb are usually sent to the Urgent section. Example of Urgent cases include abdominal pain, neurological complaints, and difficulty breathing. Advanced diagnostic testing may be conducted in the Urgent area and, depending on the causes of the chief complaint, patients may be discharged home or to a facility or admitted into one of MGH's inpatient services. Patients who may benefit from additional diagnostic evaluation or monitoring are sent to the Clinical Decision Unit (CDU). Examples of typical symptoms and conditions that are likely to send the patient to the CDU are: atrial fibrillation, congestive heart failure, back pain, dehydration, gastroenteritis, and trauma. Half of the CDU patients are released from the hospital after treatment and further diagnosis, and the other half are either sent to an ED Observation unit or to the relevant MGH inpatient service. Patients with minor, non life-threatening injuries are routed to Fast-Track and usually discharged within 60 to 90 minutes of seeing a provider. Patients under the age of 19 are usually sent to the Pediatric Emergency Department (PED), and those with acute psychiatric, neuropsychiatric, and conditions related to substance-use are treated in the Acute Psychiatry Service (APS) [6].

Boarder Patients

For patients 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)[6]. 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[6].

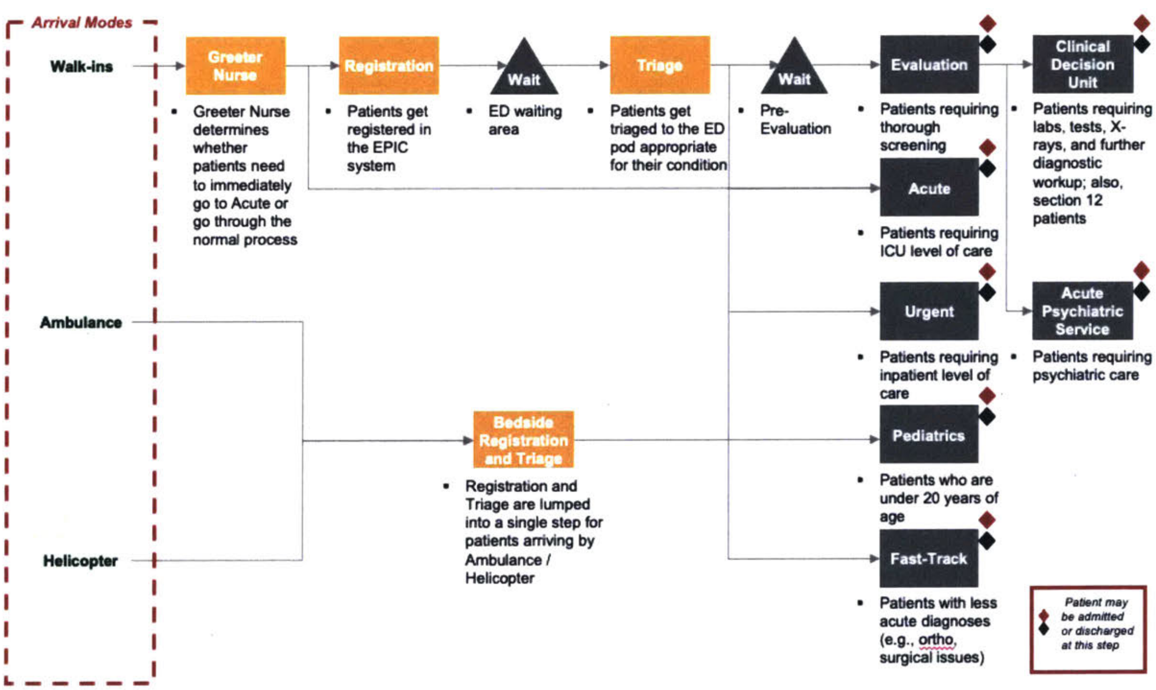

Figure 3-2: ED Process Flow Map (as of April 2018).

3.3 *Code Help* at the MGH Emergency Department

The Commonwealth of Massachusetts has established a *Code Help* policy that is mandated by the Massachusetts Department of Public Health (DPH). This policy requires hospitals to address ED overcrowding and move all admitted patients boarding in the ED to the appropriate inpatient floor within 30 minutes of activation of the *Code Help* status. *Code Help* status is reached when licensed capacity is reached and/or exceeded. Currently at MGH, the ED is responsible for triggering a *Code Help* alert hospital-wide based on predefined criteria [27]. The congestion status of the ED is tracked in the *Epic* Electronic Medical Record (EMR) system and can be:

1. *ED Open* (Green): indicates normal operating procedures in the ED.

2. *Approaching Code Help* (Yellow): indicates that the ED is becoming congested and that *Code Help* is likely to be activated in the coming few hours.

3. *Code Help* (Red): indicates that the ED's licensed capacity is reached and/or exceeded as per the DPH's directive.

4. *Capacity Disaster*: indicates a state of emergency in the ED that renders it unusable. *Capacity Disaster* is usually activated when *Code Help* fails in relieving congestion and the situation becomes unsafe for patients.

Further information on the formal definitions of congestion statuses can be found in Table 3.2.

When *Approaching Code Help*, *Code Help*, or *Capacity Disaster* levels are reached, the staff notifies ED leaders and other affiliated departments and personnel across the hospital[2]. MGH has determined several operational responses to congestion depending on its level [27].

[2]More details on those notified can be found in Appendix A.

3.3.1 *Standard Operating Procedures*

Currently, the ED holds five daily inpatient capacity meetings focusing on ED and ED Observation Unit (EDOU) patient discharges:

1. A daily Inpatient Capacity Team meeting at 10:00 AM;

2. A daily Boarder meetings between Medicine and the ED at 7:30 AM; and

3. A daily Clinical Assessment meetings with Nursing Supervisors, Admitting, and ED Resource Nurse at 8:00 AM, 12:00 PM, and 4:00 PM.

Throughout their shifts, ED clinicians round in each area of the ED to clinically assess patients waiting for dismissal to expedite discharge or admission and a Boarder Resource Nurse communicates with hospital floors regarding the transfer of boarder patients to the appropriate inpatient unit. Clinicians will only send patients with ready beds to inpatient units after receiving handoff. As soon as handoff occurs, the ED coordinator places patients on the transport board and notifies the ED Throughput Nurse. Charge Coordinators check transport status and as appropriate, patients are switched from stretchers to wheelchairs to facilitate transport. It is the Charge Coordinator's responsibility to ensure that discharges are entered in *Epic* and alert Environmental Services should there be a delay in bed / bay cleaning.

3.3.2 *Approaching Code Help*

When all 18 Acute beds become full with 2 hallway slots occupied and all 22 Urgent become full with 1 hallway slot occupied, *Approaching Code Help* status is automatically activated and the hospital-wide response team receives a page. According to the *Code Help* protocol, a communication huddle should occur between, as a minimum, the ED Acute Attending Physician, the ED Resource Nurse, and the ED Charge Coordinator; they consult with the nursing supervisor. This, however, rarely happens as these alarms have become very frequent. As a response to the alarm, ED doctors and nurses round to move patients out of Acute and all other clinical care areas of the ED. The ED Access Nurse stops transfers from outside hospitals to the ED and requests direct admission to inpatient floor.

3.3.3 *Code Help*

When all 18 Acute beds become full with 4 hallway slots occupied and all 22 Urgent become full with 3 hallway slot occupied, a communication huddle occurs between, as a minimum, the ED Acute Attending Physician, the ED Resource Nurse, and the ED Charge Coordinator; they consult with nursing supervisor. During this huddle, it is decided whether or not *Code Help* status should be activated. According to ED providers and administrators, *Code Help* is activated if the situation in the ED is deemed unsafe, either because Urgent and Acute care areas are too congested or because the patient population is exceedingly sick. According to the *Code Help* protocol, ED clinicians need to assess the Acute area patients to find any patients who are medically safe to move. If they find no movers, *Code Help* is activated and a page is sent out to the response team. If there are movers, ED clinicians ask themselves the following questions:

- Does the ED have the manpower/ staffing to safely treat the patients?
- Can the ED safely take another critical patient?
- Is the environment/facility/equipment (availability of monitors) safe to treat and continue to accept patients? (e.g., flood or other compromise)

If any ED Attending, nurse, or admin team responds *no* to these safety questions, *Code Help* status should be activated and a page should be sent out to the response team.

When *Code Help* is activated, the ED Access Nurse stops transfers from outside hospitals to the ED and requests direct admission to inpatient floor. Direct admits to inpatient units and hospital-to-hospital transfers are evaluated by the Inpatient Access Center. Within 15 minutes of *Code Help* activation, Admitting and the ED staff review cases to be admitted and meet to address capacity issues; the Administrator on Call (AOC) is included. The ED staff prepares to move boarders to inpatient units: they add Transport Assistants and request help from MGH Central Transport and Volunteer Service if necessary. The ED staff also consults Case Management to place patients directly from ED to other hospital EDs or other alternative pathways such as home hospital.

3.3.4 *Capacity Disaster*

According to the *Code Help* protocol, *Capacity Disaster* should be activated if boarders remain in the ED 2 hours after *Code Help* is paged out or if the ED is overwhelmed beyond resources available for safe patient care. However, ED decision-makers will mostly hold off on activating *Capacity Disaster* even if boarders remain in the ED 2 hours after *Code Help* as long as they deem the situation to be under control. Similar to the *Code Help* decision, a communication huddle takes place between, as a minimum, the ED Acute Attending Physician, the ED Resource Nurse, and the ED Charge Coordinator; they consult with the nursing supervisor.

When *Capacity Disaster* is activated, it gets paged out to the response team. All interventions previously identified for *Code Help* are continued and a 7 AM meeting occurs the next day if *Capacity Disaster* alert is sent after 5 PM.

All records of Emergency Department Status are tracked within *Epic*. The Emergency and Admitting departments deactivate *Code Help* / *Capacity Disaster* status when all inpatient boarders are placed and send a page indicating that *Code Help* / *Capacity Disaster* has expired. As soon as possible after the capacity status has been deactivated, a debriefing session is conducted to evaluate the response. This discussion can happen during the daily Capacity Committee meeting.

3.4 Current State of *Code Help*

3.4.1 Frequency of *Code Help* Alarms

As is shown in 3-3, the number of *Approaching Code Help* alarms has been rising steadily over the last four years, while the frequency of *Code Help* alarms increasing at a slower pace. Since *Approaching Code Help* alarms are activated automatically when objective census criteria are reached, their increase at this pace indicates a stark increase in ED congestion over the last few years. The fact that the rate of conversion of *Approaching Code Help* alarms to *Code Help* is decreasing, however, suggests that the ED is becoming more strict in deciding when to activate *Code Help*.

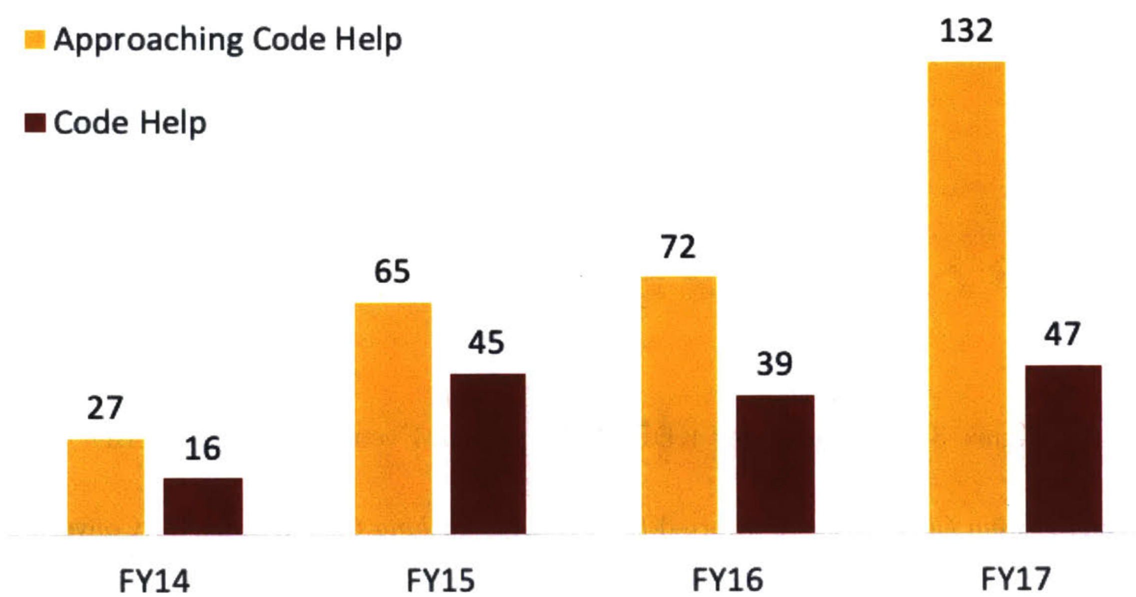

Figure 3-3: Number of *Approaching Code Help* and *Code Help* Alarms (FY14-FY17)

3.4.2 Time Distribution of Capacity Alarms

Experience suggests that capacity alarms cluster close to the middle of the day. In order to verify this, we extract the hour of occurrence of all *Approaching Code Help*, *Code Help*, and *Capacity Disaster* events from the *EDStatus* table in the *D4Q* database. We split *Approaching Code Help* events into those that eventually convert to *Code Help* and those that do not. We also split the *Code Help* events into those that get converted from *Approaching Code Help* and those that get called from *ED Open* status. We employ the Pandas Kernel Density Estimation function to estimate the Probability Density Function of the distribution of times of incidence of these alarms assuming Gaussian kernels. We examine all alarms that occurred between 05/01/2016 and 02/28/2018.

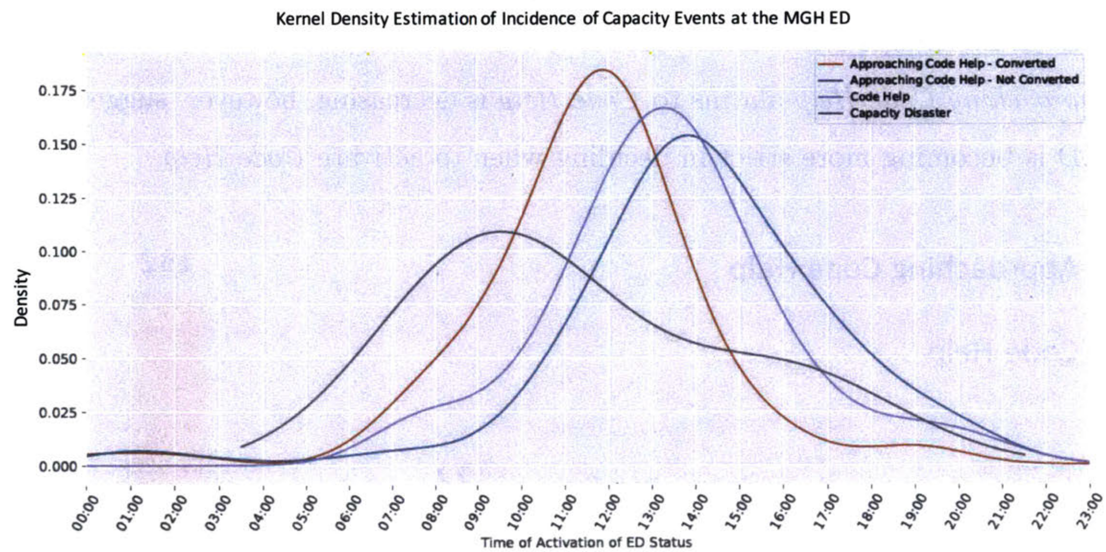

Figure 3-4: Time of day KDE of Congestion Events at the MGH ED

Approaching Code Help – Converted (N=79); *Approaching Code Help* – Not Converted (N=161); *Code Help* (N=94); *Capacity Disaster* (N=7).

Figure 3-4 suggests that *Approaching Code Help* events that end up converting to *Code Help* generally occur earlier in the day than those that get extinguished without converting, with a PDE estimate that peaks at 12:00 PM for the former type of alarm and 2:00 PM for the latter. The later an *Approaching Code Help* alarm is triggered, the more likely it is that afternoon inpatient discharges might have started to pick up their pace (see Figure 3-5), and the less likely it is to eventually convert to *Code Help*. *Code Help* alarms seem to peak in between, at about 1:20 PM.

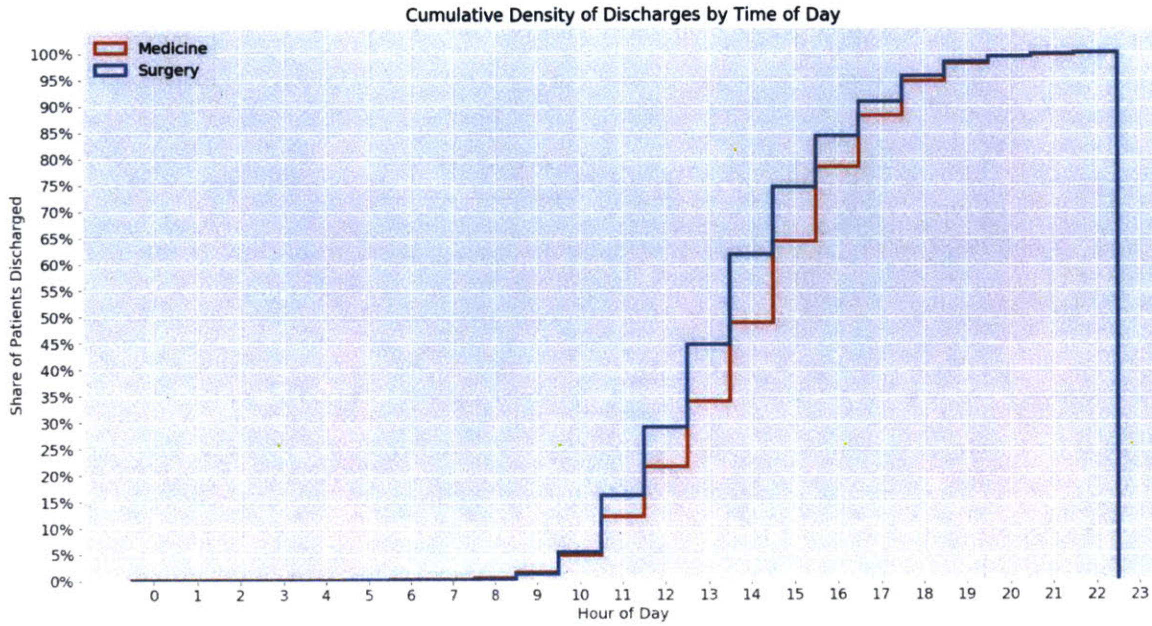

Figure 3-5: Cumulative Density Function of Discharges by Time of Day

3.4.3 Alarm Conversion

Further, we examine the number of times *Code Help* Objective Criteria[3] were reached, leveraging data from the *EDStatus* that sits in the *D4Q* database between 05/01/2016 and 12/31/2017. We split the distributions according to whether *Approaching Code Help* was later called or *ED Open* status was restored.

[3]Acute beds are full (18) with 4 hallway slots occupied and Urgent is full (22) with 3 hallway slots occupied.

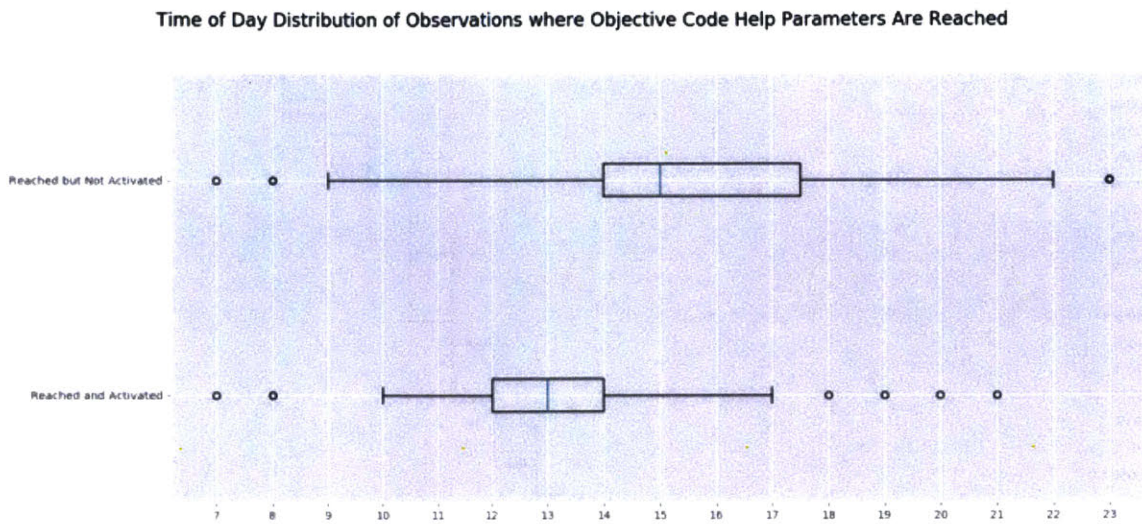

Figure 3-6: Reaching *Code Help* Objective Criteria (*Code Help* Activated vs. Not Activated) by Time of Day

Code Help Objective Criteria Reached and Converted (N=67); *Code Help* Objective Criteria Reached and not Converted (N=200)

Figure 3-6 paints a similar picture to Figure 3-4, suggesting that of the times *Code Help* Objective Criteria were reached, conversions occurred more frequently earlier in the day rather than later.

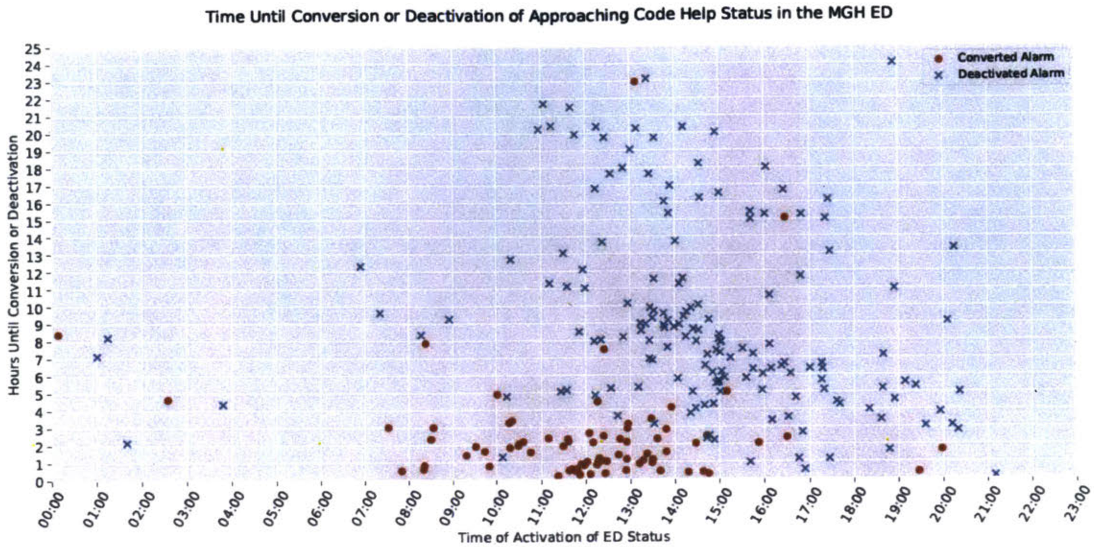

Figure 3-7: Time Until Conversion or Deactivation of *Approaching Code Help* Status in the MGH ED

Approaching Code Help – Converted (N=79); *Approaching Code Help* – Not Converted (N=161)

In Figure 3-7, we plot the time of activation of *Approaching Code Help* versus the time in hours until the alarm got converted or deactivated without conversion. The figure suggests that 89% of *Approaching Code Help* alarms that end up converting to *Code Help* do so within three hours of their activation, with the rate of conversion becoming minimal after 3:00 PM.

In Figure 3-8, we plot a frequency histogram of the distribution of time (in hours) between reaching *Code Help* Objective Criteria and the activation of *Code Help* status in the ED, considering all occurrences between 05/01/2016 and 12/31/2017. We pull this data from the *EDStatus* table in the *D4Q* database. We observe that 10% of the time, *Code Help* is called before Objective Criteria are reached. Also, 52% of the time, *Code Help* is called within an hour of Objective Criteria being reached.

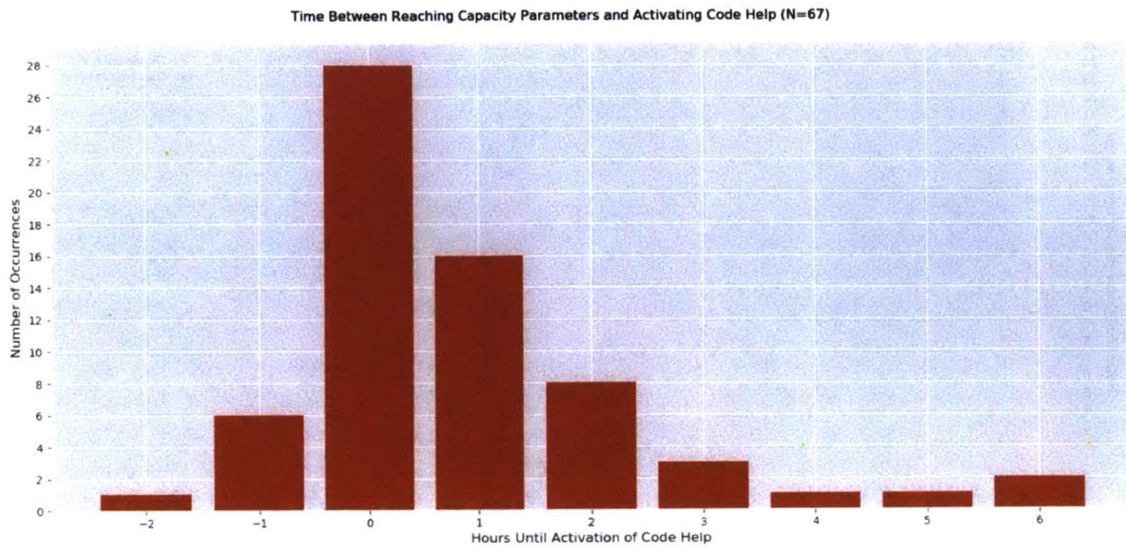

Figure 3-8: Distribution of Time (in hours) Until Activation of *Code Help* After Reaching Objective Criteria in the MGH ED

Code Help Events (N=67)

3.4.4 Day-of-week Distribution of *Code Help* Alarms

In order to gain an understanding of the relationship between the day of the week and the frequency of occurrence and rate of conversion of *Code Help* alarms, we utilize the same data to construct a histogram describing the frequency of occurrence of instances where *Code Help* Objective Criteria are reached by day-of-week and the rate at which they convert to *Code Help*.

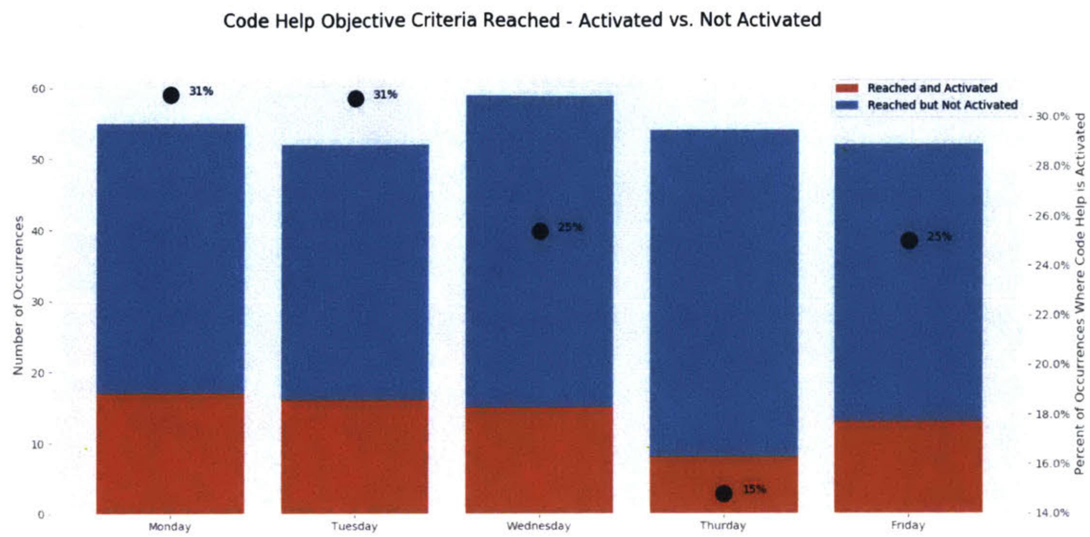

Figure 3-9: Conversion to *Code Help* After Objective Criteria Are Reached in the MGH ED – Day-of-week view

Code Help – Converted (N=67); *Code Help* Objective Criteria Reached (N=267)

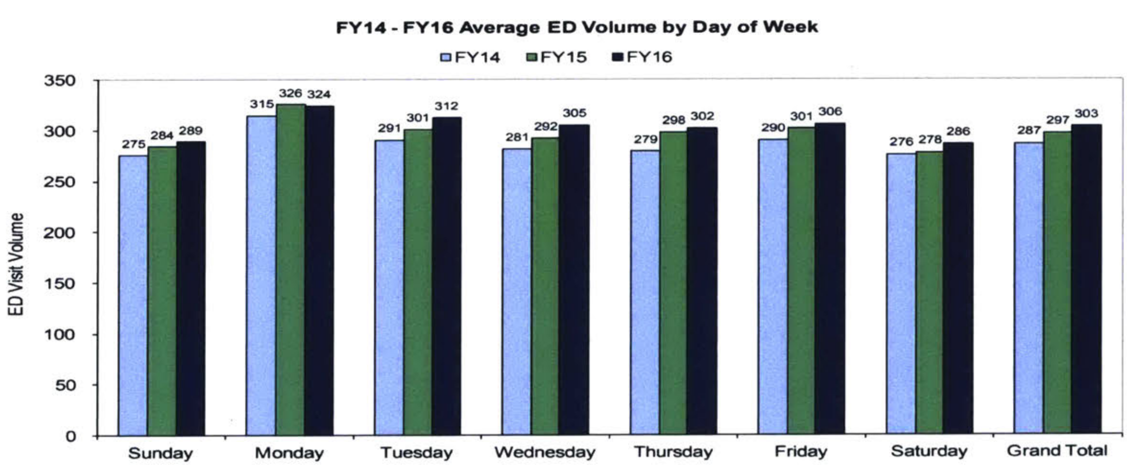

Figure 3-10: FY14-FY16 Average ED Arrival Volume by Day-of-Week

Figure 3-9 indicates that the distribution of reaching the *Code Help* Objective Criteria is almost uniform by day-of-week. However, conversion to *Code Help* was most likely on Mondays and Tuesdays (31%), second most likely on Wednesdays and Fridays (25%), and least likely on Thursday (15%). One explanation for the high conversion rate on Mondays and Tuesdays could be that the highest number of ED arrivals generally occur on those days (see Figure 3-10). The 25% conversion rate on Friday might be explained by the inpatient discharge rate being lower towards the beginning of the weekend.

Table 3.2: Emergency Department Status Description

ED Status	Description	Required Actions	Who Determines
ED Open	There are empty (monitored) beds and hallway slots in Acute and Urgent	• Standard Procedures	N/A
Approaching Code Help	Acute beds are full (18) with 2 hallway slots occupied and Urgent is full (22) with 1 hallway slot occupied	• Admitting will assign patients to off-service/non-traditional units • Reevaluates hospital-to-hospital transfers • Stops ED-to-ED transfers • Nursing ensures all licensed beds are staffed	Automatic status change based on *Epic* patient count; Charge Coordinator sends out page
Code Help	Acute beds are full (18) with 4 hallway slots occupied and Urgent is full (22) with 3 hallway slots occupied	• Admitting holds meeting; pages are sent to provider community • Infection control reviews bed closures • Case Management identifies patients for transfer out • Procedural areas reevaluate all elective admissions • Boarders are prepared to move to units	Huddle; Acute Attending & Resource Nurse have final say; Charge Coordinator sends out page
Capacity Disaster	Boarders remain in the ED 2 hours after calling *Code Help*, or if unrelated to *Code Help*, the ED is overwhelmed beyond resources available for safe patient care	• Incident commander is appointed and meeting is conducted • Bed assignment rules are altered • Full capacity protocol is implemented	Huddle; Acute Attending & Resource Nurse have final say; Charge Coordinator sends out page

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Chapter 4

Classification of *Code Help* Events

In order to diagnose the status of the hospital during *Code Help* events and gain an objective understanding of drivers behind ED congestion at Massachusetts General Hospital, we attempt to characterize *Code Help* events using k-means clustering by separating them into different classes. Our hypothesis is that some events will be ED-driven while other will be hospital-driven. To achieve this, we first perform an exploratory analysis of clinical and operational features in order to identify those that are descriptive of *Code Help*. We consider *Code Help* events between 05/01/2016 and 07/31/2017 to be our observations and examine a list of features occurring in the hour leading up to each *Code Help* event.

4.1 Exploratory Analysis of Relevant Features

We generated an initial list of features describing the operational state of the hospital. The list was compiled based on discussions with ED and inpatient physicians, nurses, and administrative staff. The features that were suggested are reported in Table 4.1 below. All subsequent analyses exclude observations occurring on weekends and holidays.

Table 4.1: List of Descriptive Features Relevant to *Code Help*

Feature	**Relevant Hospital Region**
Patient Census	Emergency Department
Number of Discharges in the Last Hour	Emergency Department, Inpatient Floors
Number of Boarders	Emergency Department
Average Boarder Wait Time[1]	Emergency Department
Patient Split by Pod	Emergency Department
Distribution of Patient Chief Complaint	Emergency Department
Patient Age Distribution	Emergency Department
Number of Critical Care Patients[2]	Emergency Department
Average Patient Acuity Score in Urgent and Acute[3]	Emergency Department
Staffing Levels	Emergency Department, Inpatient Floors
Number of Scheduled Elective Surgeries	Surgical Floors
Operational Capacity Utilization of Beds	Inpatient Floors

4.1.1 ED Patient Census

Using the *Patient Encounter* table from the *D4Q* database, we are able to identify an arrival and departure time for every patient encounter. Using this data, we determine the ED patient census at an hourly level between 05/01/2016 and 07/31/2017 by tallying, at each timepoint, the number of encounters whose arrival falls before it and

[1]The average amount of time boarder patients have been waiting in the ED so far.
[2]Patients that have had >30 min face time with an attending physician.
[3]Based on ED billing department; Level 5 for Urgent/Level 6 for Critical Care.

departure after it. We examine this feature around the time of capacity alarms (i.e. *Approaching Code Help*, *Code Help*, *Capacity Disaster*) and record our observations.

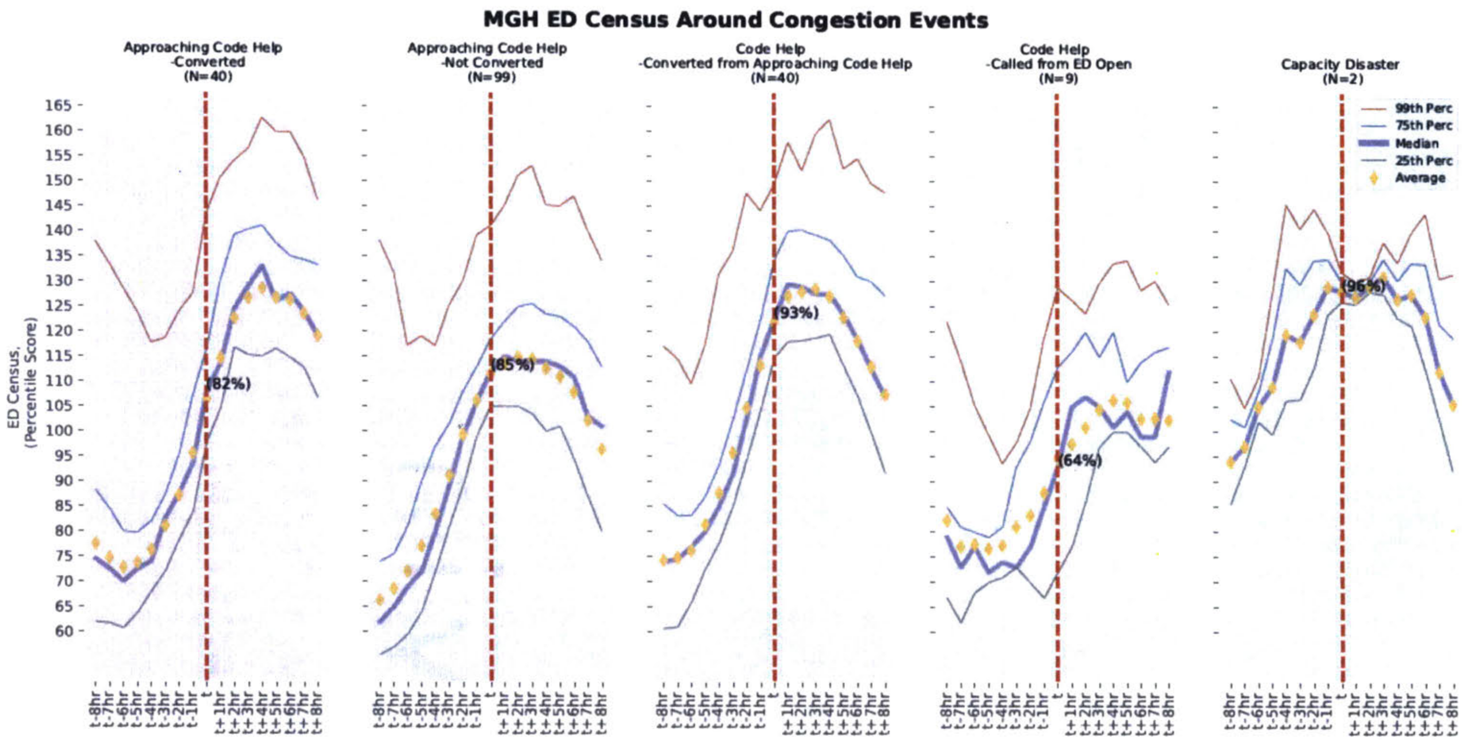

Figure 4-1: MGH ED Patient Census Around Congestion Events.

This plot and similar subsequent plots show the 25th, 50th, 75th, and 99th percentile values of an hourly feature measured during the interval {t-8 hours, t+8 hours}, where *t* indicates the hour of the generation of the alarm (i.e. *Approaching Code Help*, *Code Help*, *Capacity Disaster*) depicted by the dashed red line. *Approaching Code Help* events are split into those that eventually convert to *Code Help* and those that are deactivated with no subsequent conversion (i.e. revert to *ED Open* status). *Code Help* events are split into those that are converted from *ED Open* and those that are converted from *Approaching Code Help* status. Percentile scores that are shown in between parentheses at the time of the alarms help locate the median value of the feature of interest at that time in a distribution of observations of that same feature on weekdays, excluding holidays, between 7 AM and 11 PM over the analysis period. The normalization method is detailed further in section 4.2.1.

Figure 4-1 suggests that, in the median case of *Approaching Code Help*, MGH ED Patient Census flattens in the no-conversion case, while it continues to climb in the case of later conversion to *Code Help.* Additionally, we notice that *Code Help* events that are converted from *ED Open* generally exhibit a lower ED Census at the time of the alarm than those that are converted from *Approaching Code Help.* As expected, we see the highest overall ED Census around *Capacity Disaster* events that occur only twice during our period of interest. Perhaps the most important insight that can be derived from Figure 4-1 is that there is a high likelihood that a relationship exists between overall ED Census and the eventual conversion of *Approaching Code Help* alarms to *Code Help.*

We use the *EDCareArea* table from the *D4Q* database in order to obtain a split of the patient encounters by pod and generate a patient census accordingly. This allows us to carve out Fast-Track and Evaluation patients and track the census of the rest of the Emergency Department around congestion event triggers. We generate an hourly census feature similarly to above, between 05/01/2016 and 02/28/2018.

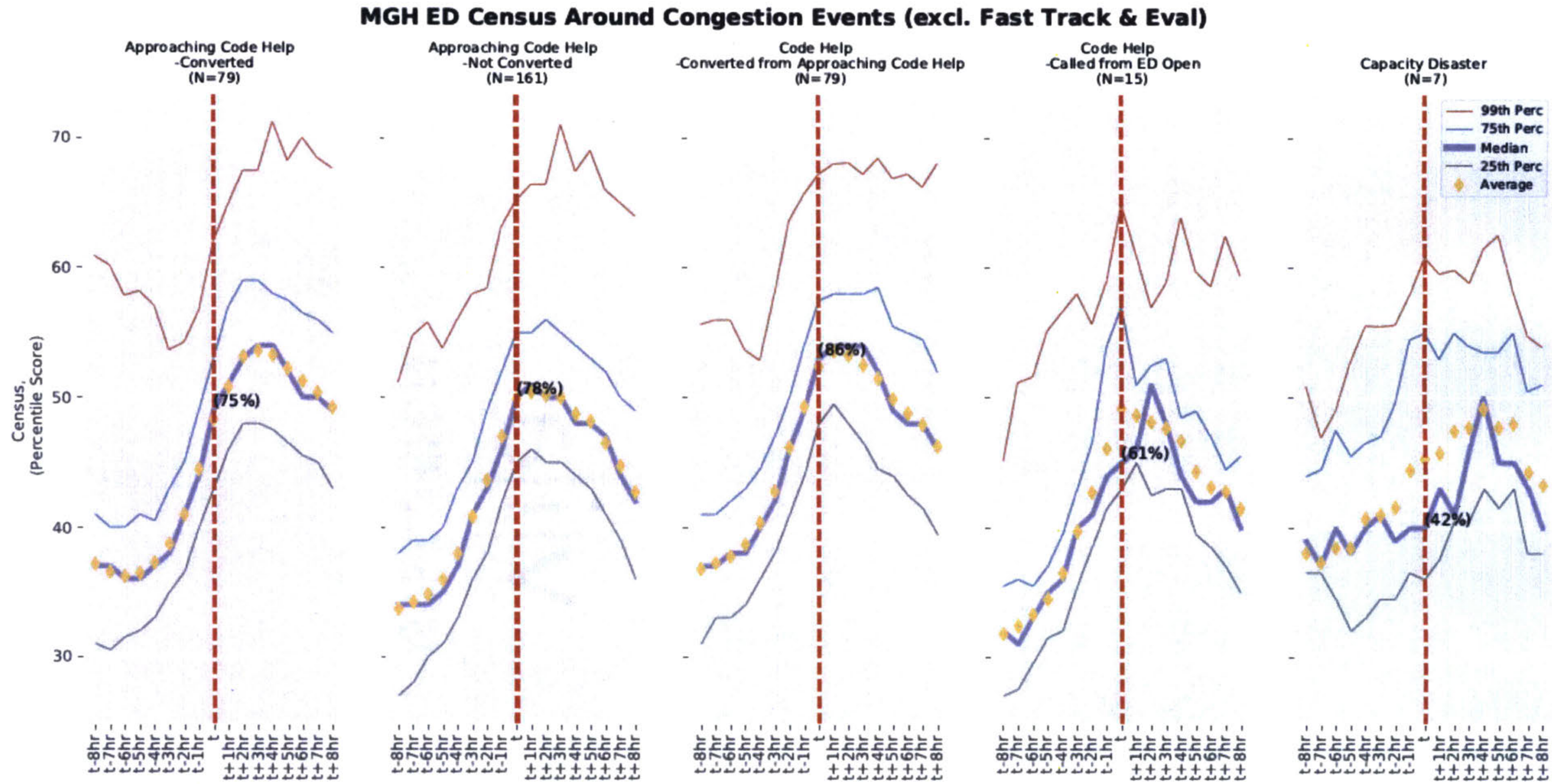

Figure 4-2: MGH ED Patient Census Around Congestion Events (Excluding Fast-Track and Evaluation).

We observe no noteworthy differences between Figure 4-1 and Figure 4-2 that can be attributed to idiosyncrasies of the Fast-Track and/or Evaluation patient population except for the case of *Capacity Disaster*, where the median census when excluding Fast Track and Evaluation pods is lower, in relative terms, than the census of the entire ED. No conclusion can be made based on this fact, however, because the number of observations of *Capacity Disaster* events is well below the threshold of statistical significance. This indicates that it is unlikely that the congestion in Fast-Track and/or Evaluation will affect the conversion of *Approaching Code Help* alarms to *Code Help*.

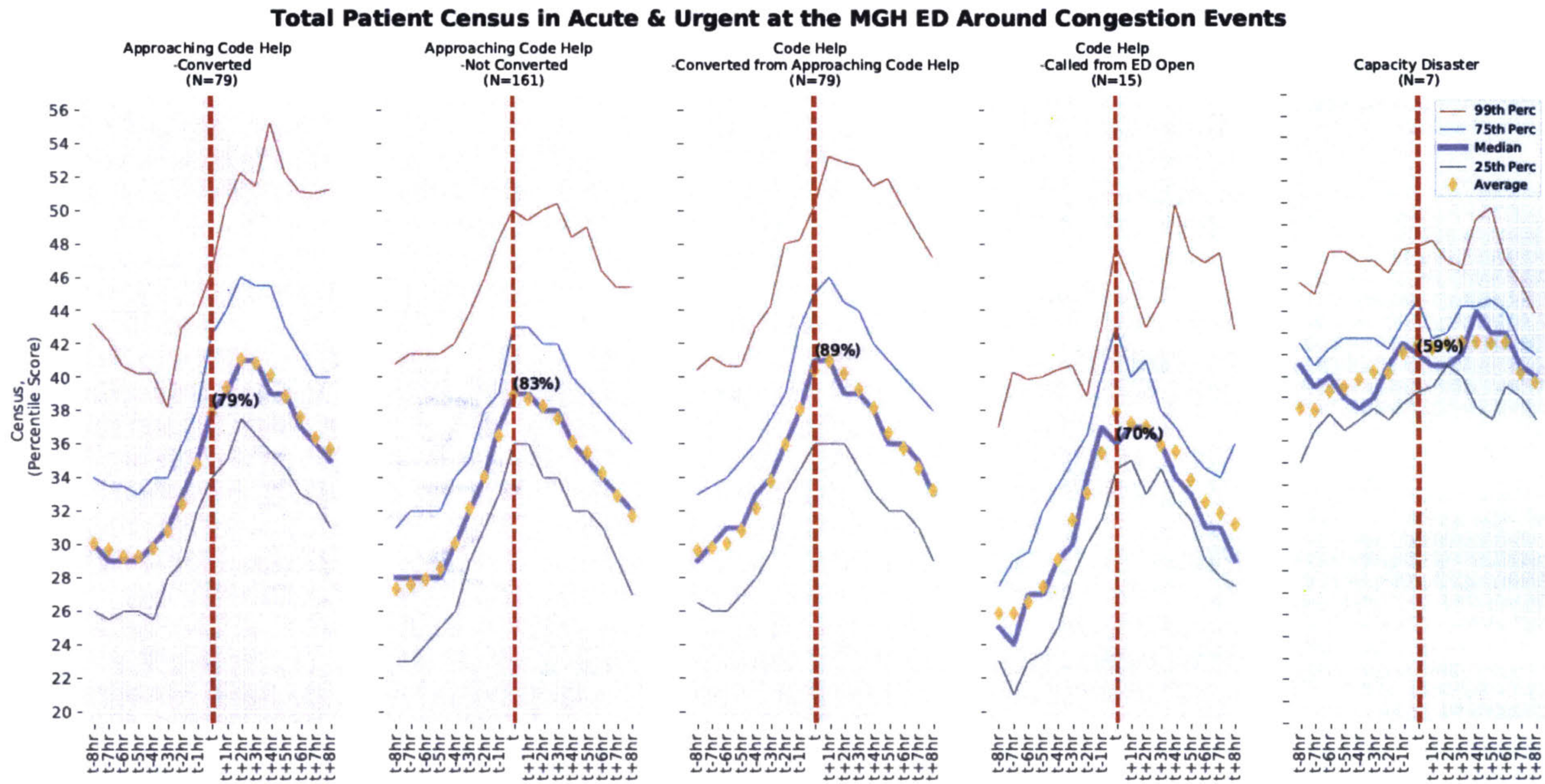

Figure 4-3: MGH ED Patient Census in Acute and Urgent Pods Around Congestion Events

Using the same data, we generate an hourly census of Urgent and Acute patients, examine it around congestion event triggers, and record our observations. Trends of this feature are found to be reasonably similar to the trends in Figure 4-1 and Figure 4-2. This confirms that the incidence of *Code Help* events is likely specifically driven by the patient census in the Urgent and Acute pods rather than that of the entire ED. Knowing this fact allows us to narrow down our focus on these two pods in the process of characterizing and predicting *Code Help* events at the MGH ED.

4.1.2 ED Patient Discharges

We define an ED Discharge to be either a discharge to their home or to a facility or a transfer to an inpatient floor[4]. Using the *Encounter* table from the *Epic ADT* database, we are able to identify discharge and transfer-out timestamps for every patient encounter. We determine the total number of ED Patient Discharges at an hourly level between 04/01/2016 and 09/30/2017, examine this feature around the time of capacity alarms (i.e. *Approaching Code Help*, *Code Help*, *Capacity Disaster*), and record our observations.

[4]Only the last discharge / transfer out within the hour is considered to eliminate the possibility of double-counting in the chance of cancellation of an order

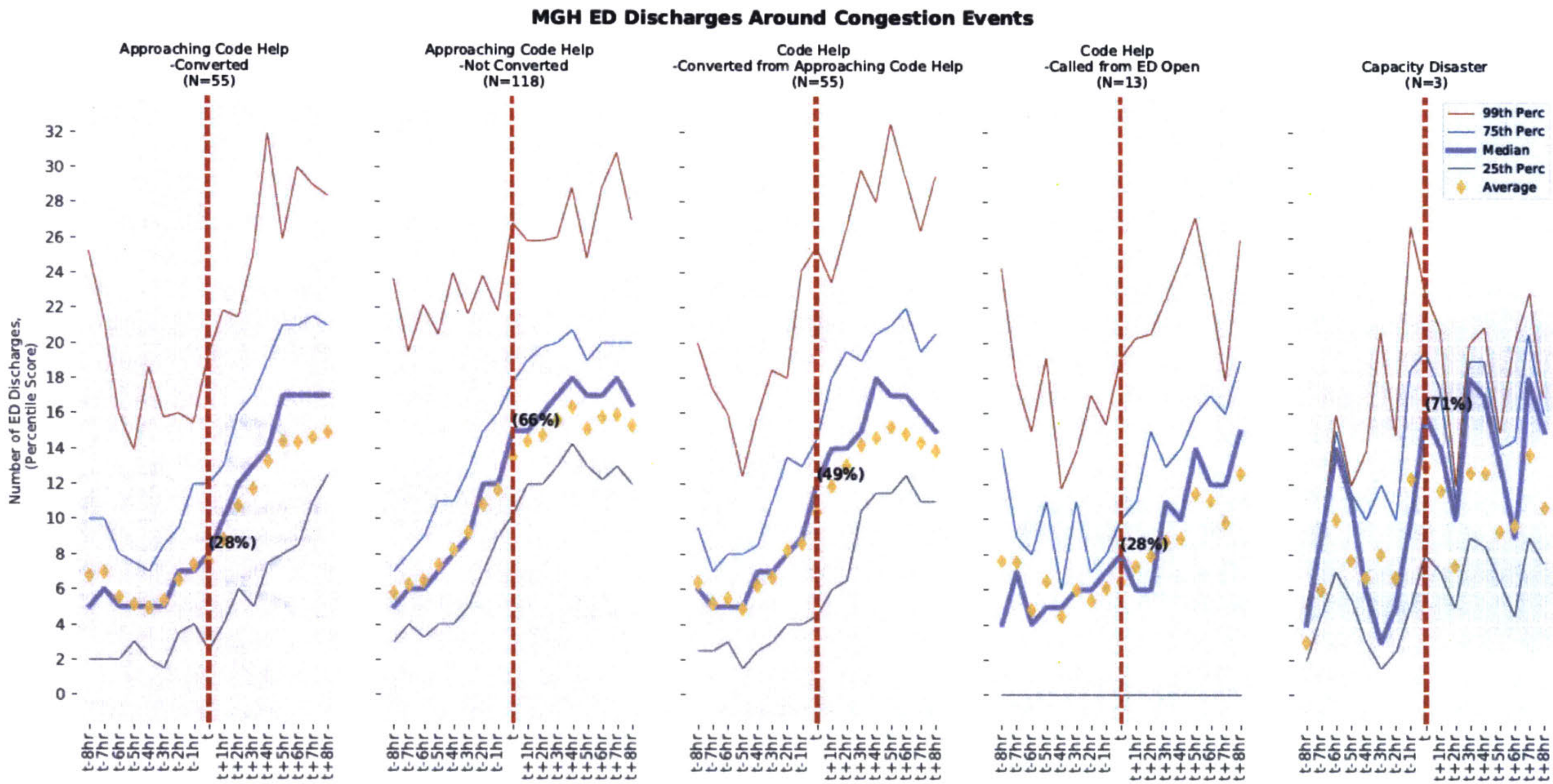

Figure 4-4: MGH ED Patient Discharges Around Congestion Events

Figure 4-4 suggests that ED Patient Discharges are generally higher during *Approaching Code Help* that do not convert than during those that do convert to *Code Help*. This feature is higher for *Code Help* events that are converted from *Approaching Code Help* than what it is for *Code Help* events that are called from *ED Open*. Finally, ED Discharges were at their highest, on median, during the three *Capacity Disaster* events that occurred during our period of interest. This suggests that there might be evidence to support the hypothesis presented to us by providers of there being a direct relationship between the number of discharges and transfers-out in the hours that follow an *Approaching Code Help* alarm and its eventual conversion to *Code Help*.

4.1.3 Inpatient Discharges

We define an Inpatient Discharge to be the discharge of a patient on an inpatient floor to their home or to a facility. Using the *Encounter* table from the *Epic ADT* database, we are able to identify inpatient discharges for every patient encounter. We determine the total number of Inpatient Discharges at an hourly level between 04/01/2016 and 09/30/2017, examine this feature around the time of capacity alarms (i.e. *Approaching Code Help*, *Code Help*, *Capacity Disaster*), and record our observations. What is most striking in Figure 4-5 is that it seems to indicate that inpatient discharge do not accelerate when *Code Help* is called as it is hoped. Additionally, the rate of inpatient discharges seems to ramp up slowly in the case of the *Approaching Code Help* events that eventually convert to *Code Help*, while for those that do not, this rate starts from a peak – on median – and declines afterwards.

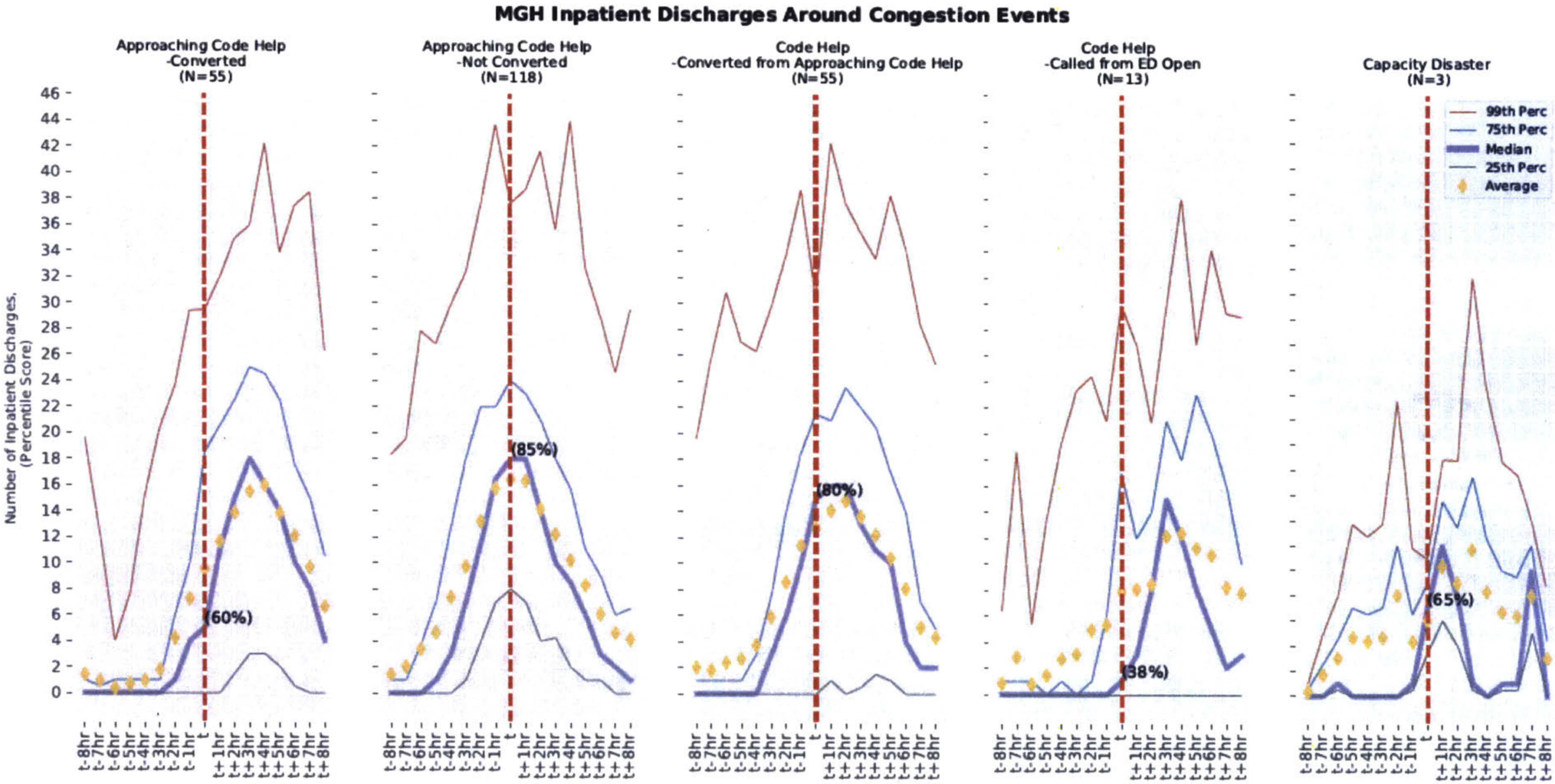

Figure 4-5: MGH Inpatient Discharges Around Congestion Events

Figure 4-5 clearly indicates that at the time of *Approaching Code Help* events that do not convert, the number of Inpatient Discharges is higher than in the case of those that do convert to *Code Help.* In the median case of *Approaching Code Help* events that do not convert, we see that the number of hourly Inpatient Discharges achieves its maximum at the time of the alarm and steadily decreases afterwards. The peaking of the total number of hourly Inpatient Discharges happens later for *Approaching Code Help* events that do convert. Also, and as we would expect, the total number of Inpatient Discharges is generally higher during *Code Help* events that convert from *Approaching Code Help* than for those that convert from *ED Open.*

4.1.4 ED Boarder Patients Census

ED patients who have been admitted to the hospital and have been waiting for a bed for longer than two hours are called boarder patients. We are able to tally their numbers using the *EDCareArea* table from the *D4Q* database and create a feature containing the total number of Boarder patients in the ED at each hour between 05/01/2016 and 02/28/2018. We examine this feature around the time of capacity alarms (i.e. *Approaching Code Help*, *Code Help*, *Capacity Disaster*), and record our observations.

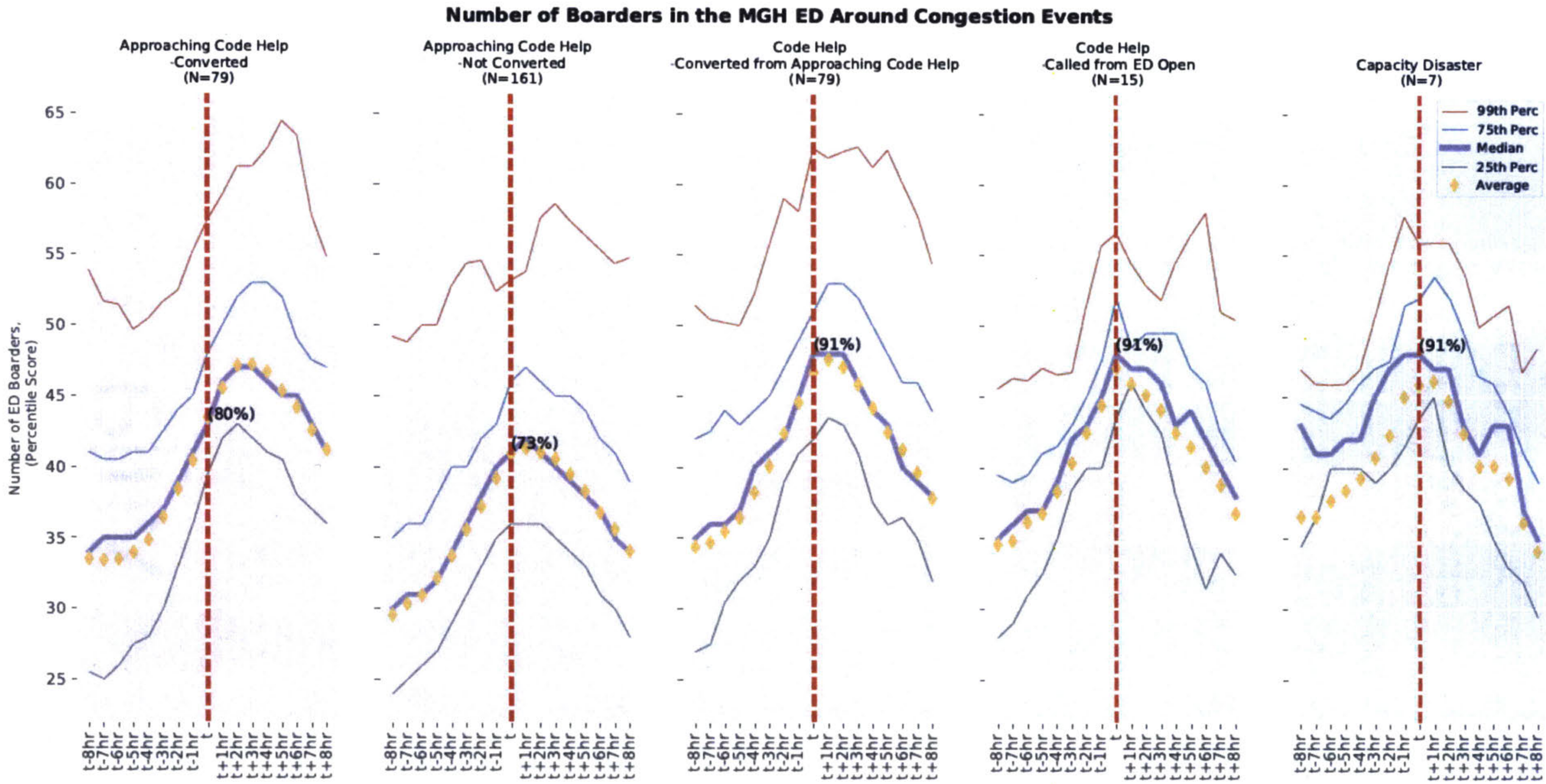

Figure 4-6: MGH Boarder Patients Around Congestion Events

Figure 4-6 indicates that the median number of boarders at the time of *Approaching Code Help* is higher for those events that eventually convert to *Code Help* than for those that get extinguished without converting. Additionally, the median number of boarders peaks 2-to-3 hours after the alarm for events that convert; it peaks at around the time of the alarm for *Approaching Code Help* events that do not convert to *Code Help*. The median number of boarders starts declining within the hour of *Code Help* and *Capacity Disaster* alarms being triggered. We notice very similar trends if we consider Medicine boarders[5] alone as can be seen in Figure 4-7 below.

[5] Boarders who are waiting for beds on the following Inpatient Floors:
MGH BLAKE 11 PSYCH; MGH BLAKE 13 OB; MGH ELLISON 10 STP DWN; MGH ELLISON 11 CARD INT; MGH ELLISON 16 MED; MGH ELLISON 17 PEDI; MGH ELLISON 18 PEDI; MGH ELLISON 19 THOR MED; MGH BIGELOW 9 RACU MED; MGH BIGELOW 9 MED; MGH BIGELOW 11 MED; MGH LUNDER 7 NEURO; MGH LUNDER 8 NEURO; MGH LUNDER 9 ONCOLOGY; MGH LUNDER 10 ONCOLOGY; MGH PHILLIPS 20 MED; MGH PHILLIPS 22 S/M/O; MGH WHITE 10 MEDICINE; MGH WHITE 11 MEDICINE; MGH PHILLIPS 21 GYN; MGH WHITE 8 MEDICINE; MGH WHITE 9 MEDICINE; MGH ELLISON 12 MED.

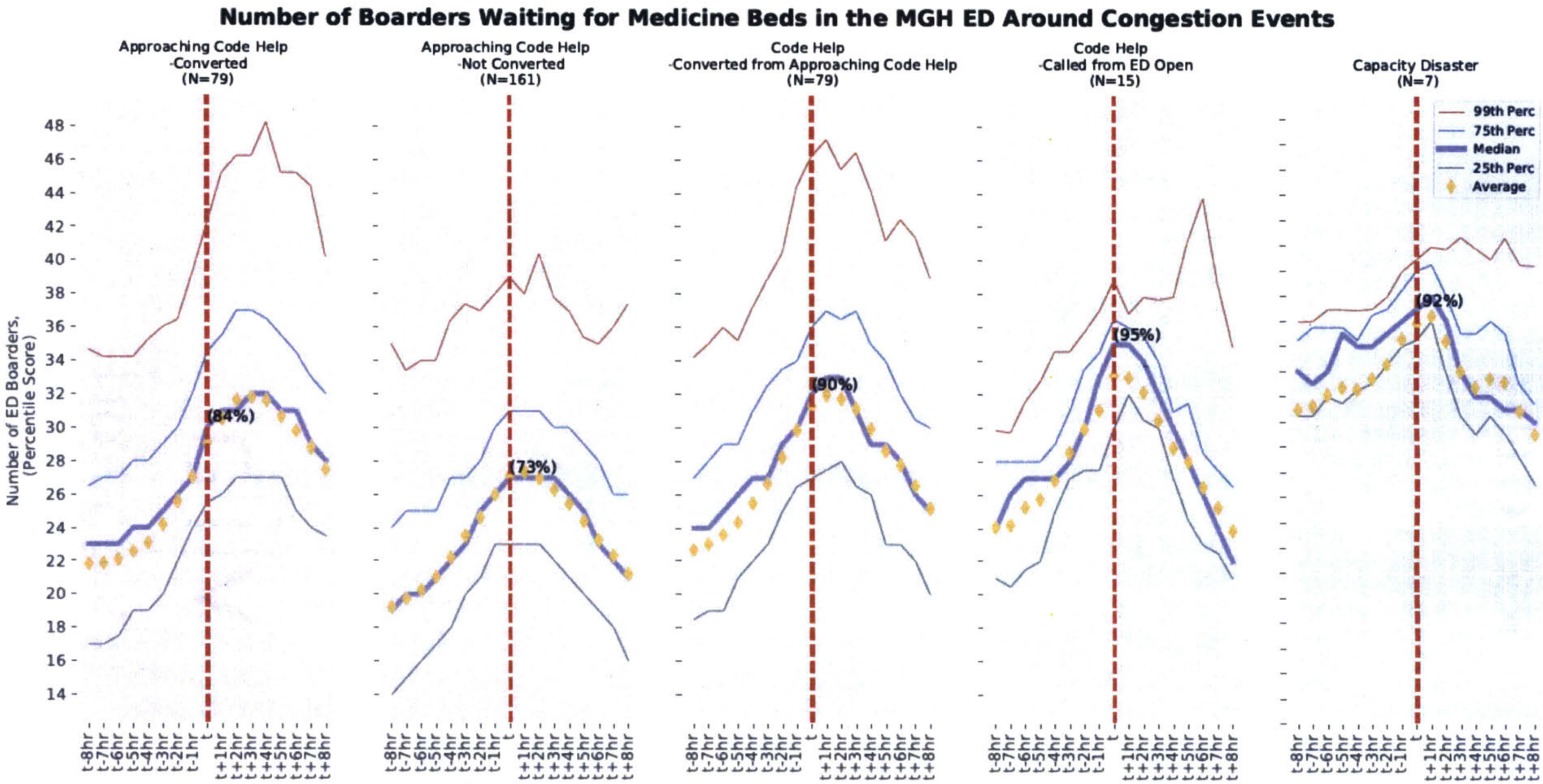

Figure 4-7: MGH Medicine Boarders Around Congestion Events

Figure 4-7 suggest that the number of Medicine boarders – a majority of all boarders – may be indicative of whether *Approaching Code Help* will eventually convert to *Code Help.* Also, it indicates that the presence of an exceedingly high number of Medicine boarders in the ED might lead to *Code Help* being called directly from *ED Open* status.

4.1.5 Average Boarding Time of Boarder Patients

In order to get an indication of how long boarder patients have been waiting at the time of congestion alarms, we calculate an average boarding time of all boarders in the ED, on an hourly basis, between 05/01/2016 and 02/28/2018. This information is pulled from the *EDCareArea* table in the *D4Q* database. We examine this feature around the time of capacity alarms (i.e. *Approaching Code Help*, *Code Help*, *Capacity Disaster*), and record our observations.

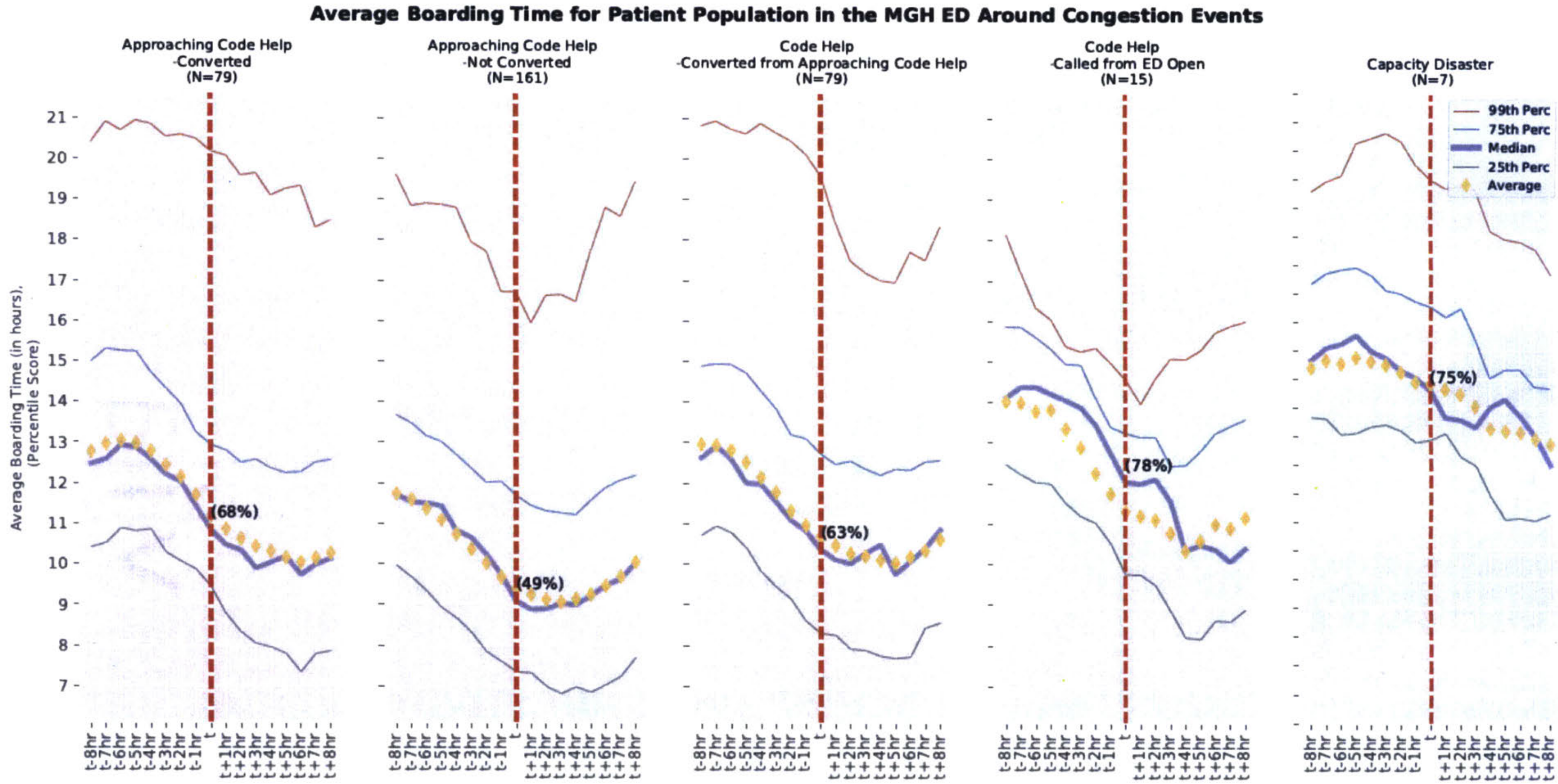

Figure 4-8: MGH Average Wait Time of Boarders Around Congestion Events

The average wait time of boarders in the median case of *Approaching Code Help* events that get converted, is 11 hours – a full two hours longer than what it is for *Approaching Code Help* events that revert back to *ED Open* without converting. In the case of *Approaching Code Help* alarms that convert, this feature continues to drop within a six hour window after the alarm until it hits its minimum of about 9.5 hours. In the case of no conversion, the average boarding time hits its minimum of 9 hours at around the time of the alarm and starts climbing again around 4 hours after that. The average wait time of the boarder population during *Code Help* alarms is, at the median, around 10.5 hours for those that are converted from *Approaching Code Help*, and 12 hours for those that are called from *ED Open*. The average wait time for the boarder patient population is, on median, 14.5 hours during *Capacity Disaster* alarms. We notice very similar trends if we consider the average wait time of Medicine boarders alone, as indicated by Figure 4-9 below.

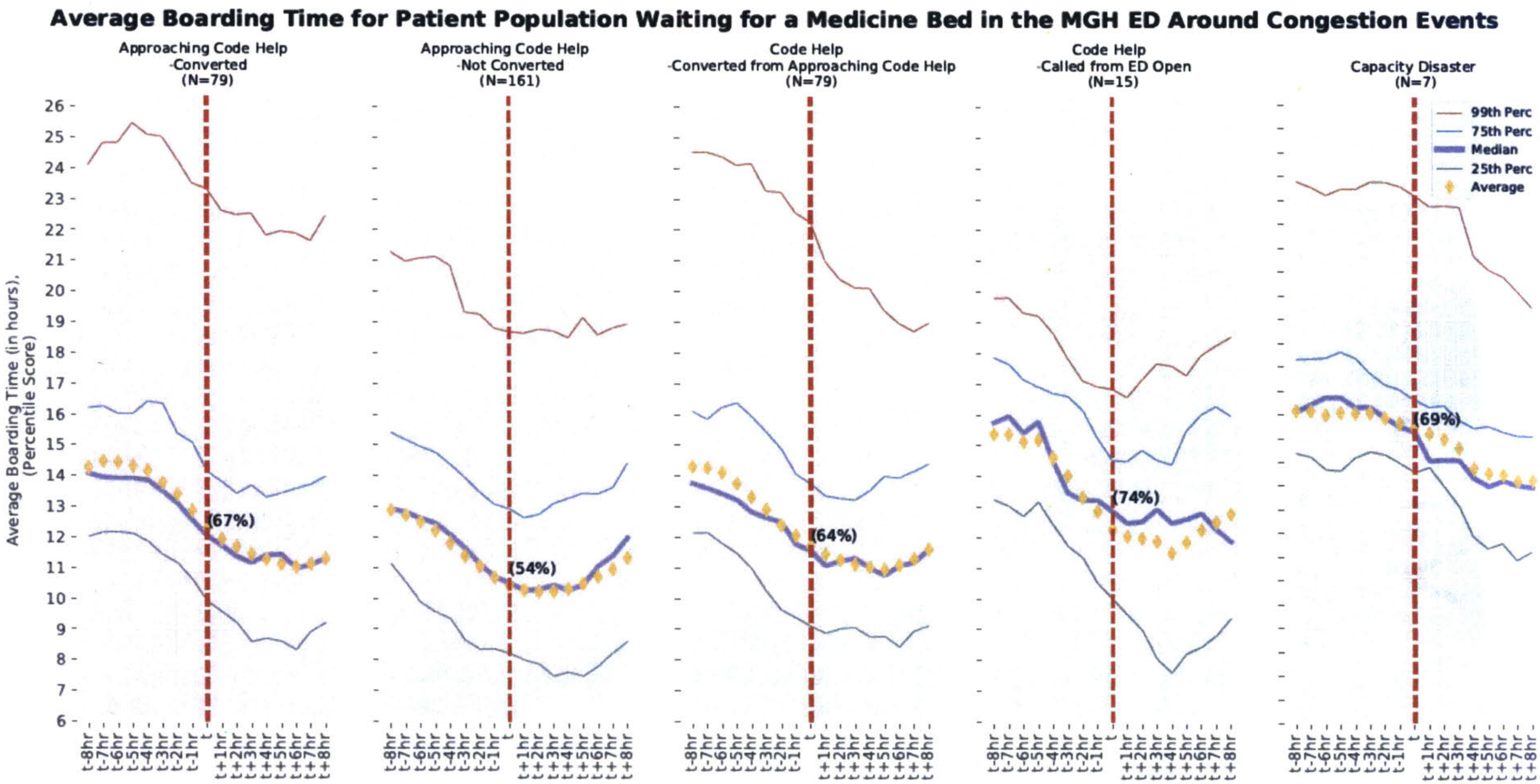

Figure 4-9: MGH Average Wait Time of Medicine Boarders Around Congestion Events

Figure 4-9 indicates that there might be a relationship between the average time boarders are waiting for a Medicine bed and the likelihood of an *Approaching Code Help* to convert to *Code Help*. The sight of boarders waiting for long time in the ED might influence *Code Help* decision-makers, leading them to trigger the alarm.

4.2 *Code Help* Clustering

In this section, we attempt to cluster *Code Help* events into separate classes in an attempt to form an objective characterization of them and understand the drivers of their occurrence. We rely on our exploratory analysis as well as on the clinical and operational experience of the ED teams in order to select the features to use for classification and employ the k-means algorithm to perform the clustering.

4.2.1 Feature Selection and Scaling

The exploratory analysis suggests that *Code Help* incidence is associated with high congestion in the ED due to a high rate of arrivals in the hour prior to *Code Help* or high bed capacity utilization on the medicine floors. It also suggests that time-of-day and day-of-week might have a high relevance to whether or not *Code Help* gets activated. In order to verify this hypothesis, we generate hourly features for ED Arrivals and Bed Capacity Utilization on Medicine floors using data from the *EDCareArea* and *Epic ADT* tables between 05/01/2016 and 09/30/2017. We group observations that occur on the same day and within the same hour to remove the effects of day-of-week and time of day seasonality and apply the following formula to generate a scaled z-score of the feature:

$$z_{d,h} = \frac{X_{d,h} - \overline{X_{d,h}}}{\sigma_{d,h}}$$

Where d is the index corresponding to each of the five weekdays and h is the index corresponding to each hour block starting with {7 AM - 8 AM} and ending with {10 PM - 11 PM}. After this process is completed, we return the features to their initial order, breaking the grouping by day and hour. This process creates features that are properly scaled and allows us to examine them more intuitively relative to what they are expected to be given a certain day-of-week and time of day.

4.2.2 K-Means Algorithm

K-means aims to partition a set of M points $(x_1, x_2, ..., x_M)$ in N dimensions into K clusters $\mathbf{S} = \{S_1, S_2, ...S_K\}$ so as to minimize the within-cluster sum of squares. More formally, it solves the following problem:

$$\underset{\mathbf{S}}{\operatorname{argmin}} \sum_{r=1}^{K} \sum_{x \in S_r} \|x - \mu_r\|^2$$

Where μ_r is the mean of the points in S_r [28].

Method

The algorithm takes in a matrix of M *Code Help* observations in N dimensions and a matrix of K initial cluster centers in N dimensions. The number of points in cluster L is denoted by $NC(L)$, and $D(I, L)$ is the Euclidean distance between point I and cluster L. The aim of the algorithm is to search fo a K-partition with locally optimal within-cluster sum of squares by moving points from one cluster into another. [29]

Step 1. For each point $I (I = 1, 2, ..., M)$, find its closest and second closest cluster centers, $IC1(I)$ and $IC2(I)$ respectively. Assign point I to cluster $IC1(I)$.

Step 2. Update the cluster centers to be the averages of points contained within them.

Step 3. Initially, all clusters belong to the live set.

Step 4. This is the optimal-transfer (OPTRA) stage:
Consider each point $I (I = 1, 2, ..., M)$ in turn. If cluster $L (L = 1, 2, ..., K)$ is updated in the last quick-transfer (QTRAN) stage, then it belongs to the live set throughout this stage. Otherwise, at each step, it is not in the live set if it has not been updated in the last M optimal-transfer steps. Let point I be in cluster $L1$. If $L1$ is in the live

set, do Step 4a; otherwise, do Step 4b.

Step 4a. Compute the minimum of the quantity, $R2 = \frac{NC(L) \times D(I,L)^2}{NC(L)+1}$, over all clusters $L(L \neq L1, L = 1, 2, ..., K)$. Let $L2$ be the cluster with the smallest $R2$. If this value is greater than or equal to $\frac{NC(L1) \times D(I,L1)^2}{NC(L1)-1}$, no reallocation is necessary and $L2$ is the new $IC2(I)$. (Note that the value $\frac{NC(L1) \times D(I,L1)^2}{NC(L1)-1}$ is remembered and will remain the same for point I until cluster $L1$ is updated.) Otherwise, point I is allocated to cluster $L2$ and LI is the new $IC2(I)$. Cluster centers are updated to be the means of points assigned to them if reallocation has taken place. The two clusters that are involved in the transfer of point I at this particular step are now in the live set.

Step 4b. This step is the same as Step 4a, except that the minimum R2 is computed only over clusters in the live set.

Step 5. Stop if the live set is empty. Otherwise, go to Step 6 after one pass through the data set.

Step 6. This is the quick-transfer (QTRAN) stage:

Consider each point $I(1 = 1, 2, ..., M)$ in turn. Let $L1 = IC1(I)$ and $L2 = IC2(I)$. It is not necessary to check the point I if both the clusters $L1$ and $L2$ have not changed in the last M steps. Compute the values $R1 = \frac{NC(L1) \times D(I,L1)^2}{NC(L1)-1}$ and $R2 = \frac{NC(L2) \times D(I,L2)^2}{NC(L2)+1}$. (As noted earlier, $R1$ is remembered and will remain the same until cluster $L1$ is updated.)

If $R1$ is less than $R2$, point I remains in cluster $L1$. Otherwise, switch $IC1(I)$ and $IC2(I)$ and update the centers of clusters $L1$ and $L2$. The two clusters are also noted for their involvement in a transfer at this step.

Step 7. If no transfer took place in the last M steps, go to Step 4. Otherwise, go to Step 6.

Optimal Number of Clusters

One of the shortcomings of K-Means is that it has to be fed the number of clusters as an input for it cannot determine it on its own. A common heuristic method that is used to validate the most suitable number of clusters is the elbow method. It relies on finding the "elbow" in a plot of the average internal Sum of Squares over a range of possible number of clusters. The average internal Sum of Squares can be written mathematically as follows:

$$W_K = \sum_{r=1}^{K} \frac{D_r}{n_r}$$

where K is the number of clusters, n_i is the number of observations in cluster i, and D_i is the sum of distances between all points in a cluster:

$$D_r = \sum_{i=1}^{n_r-1} \sum_{j=i}^{n_r} \|d_i - d_j\|$$

4.2.3 Clustering Results

We generate the average internal Sum of Squared Errors (SSE) for K in the range 1 to 14 and plot it in Figure 4-10 below. The number of clusters at the elbow beyond which we start seeing diminishing returns is 3 (SSE = 42). We notice from the figure that the curve is rather smooth, which suggests that the data does not cluster exceptionally well, but good enough for the purposes of our analysis. This can also be seen in the scatter plot of Figure 4-11.

Optimal Number of Clusters

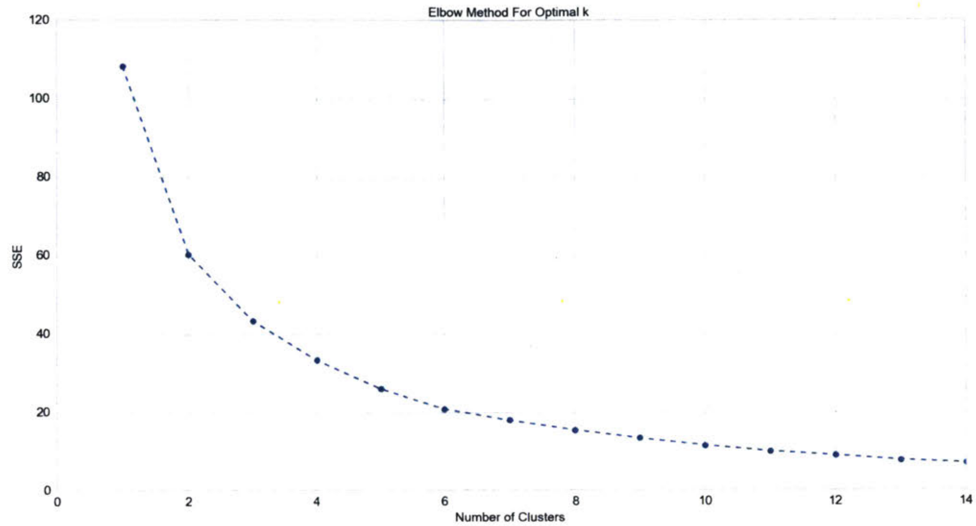

Figure 4-10: Elbow Method to Determine Optimal Number of Clusters

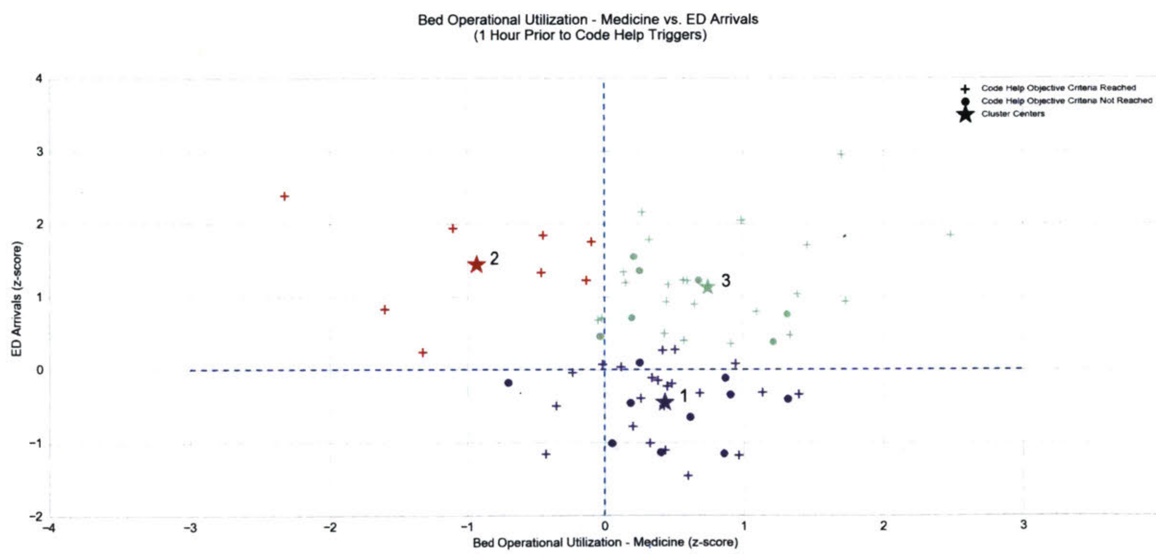

Figure 4-11: Clustering of ED Arrivals vs. Bed Operational Capacity Utilization of Medicine Beds in the Hour Leading Up to *Code Help* Events at the MGH ED

Code Help Events (N=67)

Table 4.2: Cluster Centers

Cluster Centers	**Bed Op. Cap. Util.**	**ED Arrivals**	***Code Help* Type**	**Frequency**
1	0.432	-0.448	High Cap. Util, Low Arrivals	46%
2	-0.933	1.450	Low Cap. Util, High Arrivals	12%
3	0.739	1.130	High Cap. Util, High Arrivals	42%

4.2.4 Discussion of Results

As we can see in Table 4.2, Class 1 exhibits a Bed Operational Capacity Utilization that is 0.43 standard deviations above the mean and ED Arrivals that are 0.44 standard deviations below the mean, relative to the time of day and day-of-week. In this class of *Code Help* events, the medicine floors are, on average, busier than expected and the arrivals into the ED are lower than expected. Class 1 makes up 46% of observations. Class 2 exhibits a Bed Operational capacity Utilization 0.93 standard deviations below the mean and ED arrivals 1.45 standard deviations above the mean, relative to the time of day and day-of-week. For this type of *Code Help* events, the medicine floors are less busy than expected but there is a surge in ED arrivals. Class 2 makes up 12% of observations. Class 3 exhibits a Bed Operational Capacity Utilization that is 0.74 standard deviations above the mean and ED Arrivals that are 1.13 standard deviations above the mean, relative to the time of day and day-of-week. Class 3 events occur when the ED sees a surge in arrivals while the medicine floors are busy. Class 3 makes up 42% of observations. Based on this analysis, it seems like downstream congestion is a bigger problem than a high rate of ED arrivals when it comes to the frequency of incidence of *Code Help*.

4.3 Congestion Dashboard

In order to help better understand the drivers behind *Code Help* events, we devised a visualization dashboard that, if implemented, would allow the ED team and hospital leadership to troubleshoot congestion in real-time and initiate targeted corrective actions. This dashboard allows the user to view key ED and hospital-related operational metrics, both in absolute terms and relative[6] to what one expects them to be during a certain hour and on a certain day-of-week. Additionally, it will allow the user to compare the relative metrics to their average across all instances of *Code Help*. Table 4.3 contains a thorough description of all the dashboard features.

Table 4.3: Congestion Dashboard Feature Description

Feature	**Description**
Acute Score	The acuity score is a categorical variable used by the ED Billing department that can take values 1 (least acute) to 6 (most acute). This feature represents the average acuity score of patients in the Acute pod of the ED. It is currently used retroactively since there were no indicators of patient acuity that could be pulled in real-time at the time this research is conducted.
Acute Census	The patient census in the Acute pod of the ED.
Urgent Census	The patient census in the Urgent pod of the ED.

[6]Normalization method is explained in section 4.2.1.

Table 4.3: Congestion Dashboard Feature Description

Feature	**Description**
Urgent and Acute Hourly Accumulation	The number of patients entering the Urgent and Acute pods minus the number of patients leaving the Urgent and Acute pods in the last hour.
Bed Operational Utilization – Medicine	The operational utilization of beds on Medicine floors[7]. It is calculated as the ratio of utilized beds to available beds on Medicine floors (i.e. total beds minus beds that are blocked for maintenance, infection control, a disruptive patient, or any other reason).
Bed Operational Utilization – Surgery	The operational utilization of beds on Surgical floors[8].
Bed Operational Utilization – ICU	The operational utilization of beds on ICU floors[9].
Number of Occupied Beds – Medicine	The number of beds that are occupied by patients and hence unavailable on Medicine floors.

[7]MGH Blake 11 Psych; MGH Blake 13 Ob; MGH Ellison 10 Stp Dwn; MGH Ellison 11 Card Int; MGH Ellison 16 Med; MGH Ellison 17 Pedi; MGH Ellison 18 Pedi; MGH Ellison 19 Thor Med; MGH Bigelow 9 RACU Med; MGH Bigelow 9 Med; MGH Bigelow 11 Med; MGH Lunder 7 Neuro; MGH Lunder 8 Neuro; MGH Lunder 9 Oncology; MGH Lunder 10 Oncology; MGH Phillips 20 Med; MGH Phillips 22 S/M/O; MGH White 10 Medicine; MGH White 11 Medicine; MGH Phillips 21 Gyn; MGH White 8 Medicine; MGH White 9 Medicine; MGH Ellison 12 Med.

[8]MGH Blake 6 Transplant; MGH Ellison 6 Orth; MGH Ellison 7 Surg; MGH Ellison 8 Cardsurg; MGH Bigelow 14 Vasc; MGH White 6 Ortho; MGH White 7 Gen Surg; MGH Ellison 14 Plastcs

[9]MGH Blake 7 MICU; MGH Blake 8 Card SICU; MGH Blake 12 ICU; MGH Ellison 4 SICU; MGH Ellison 9 Med; MGH Bigelow 6 PICU; MGH Lunder 6 Neuro ICU; MGH Blake 10 NICU; MGH Ellison 14 Brn ICU; MGH Bigelow 13 RACU

Table 4.3: Congestion Dashboard Feature Description

Feature	Description
Number of Occupied Beds – Surgery	The number of beds that are occupied by patients and hence unavailable on Surgical floors.
Number of Occupied Beds – ICU	The number of beds that are occupied by patients and hence unavailable on ICU floors.
Number of Blocked Beds – Medicine	The number of beds that are blocked for maintenance, infection control, a disruptive patient, or other reasons and hence unavailable on Medicine floors.
Number of Blocked Beds – Surgery	The number of beds that are blocked for maintenance, infection control, a disruptive patient, or other reasons and hence unavailable on Surgical floors.
Number of Blocked Beds – ICU	The number of beds that are blocked for maintenance, infection control, a disruptive patient, or other reasons and hence unavailable on ICU floors.
Pending Medicine Bed Requests	The number of bed requests made for patients currently in the ED for beds on Medicine floors.
Pending Surgery Bed Requests	The number of bed requests made for patients currently in the ED for beds on Surgical floors.

Table 4.3: Congestion Dashboard Feature Description

Feature	**Description**
Pending ICU Bed Requests	The number of bed requests made for patients currently in the ED for beds on ICU floors.
Share of Non-ED Bed Requests – Medicine	The share of overall bed requests made on Medicine floors that do not originate from the ED. These requests compete with ED requests.
Share of Non-ED Bed Requests – Surgery	The share of overall bed requests made on Surgical floors that do not originate from the ED. These requests compete with ED requests.
Share of Non-ED Bed Requests – ICU	The share of overall bed requests made on ICU floors that do not originate from the ED. These requests compete with ED requests.

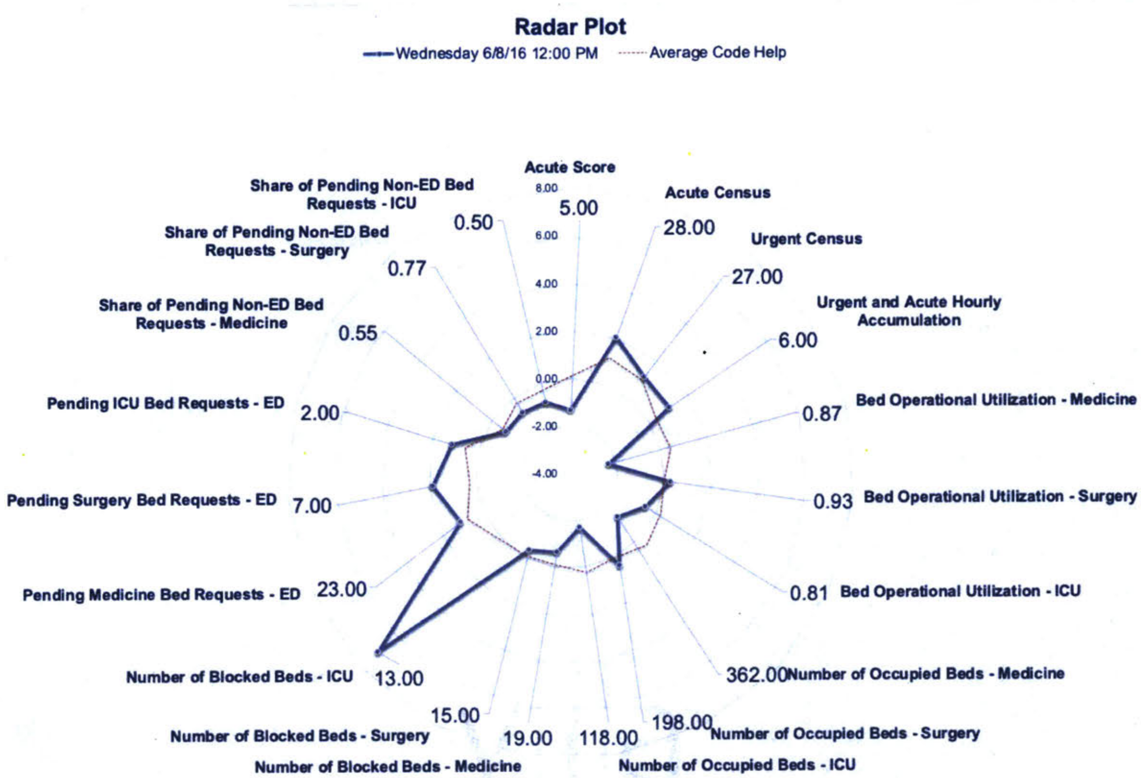

Figure 4-12: Code Help Dashboard – Example 1

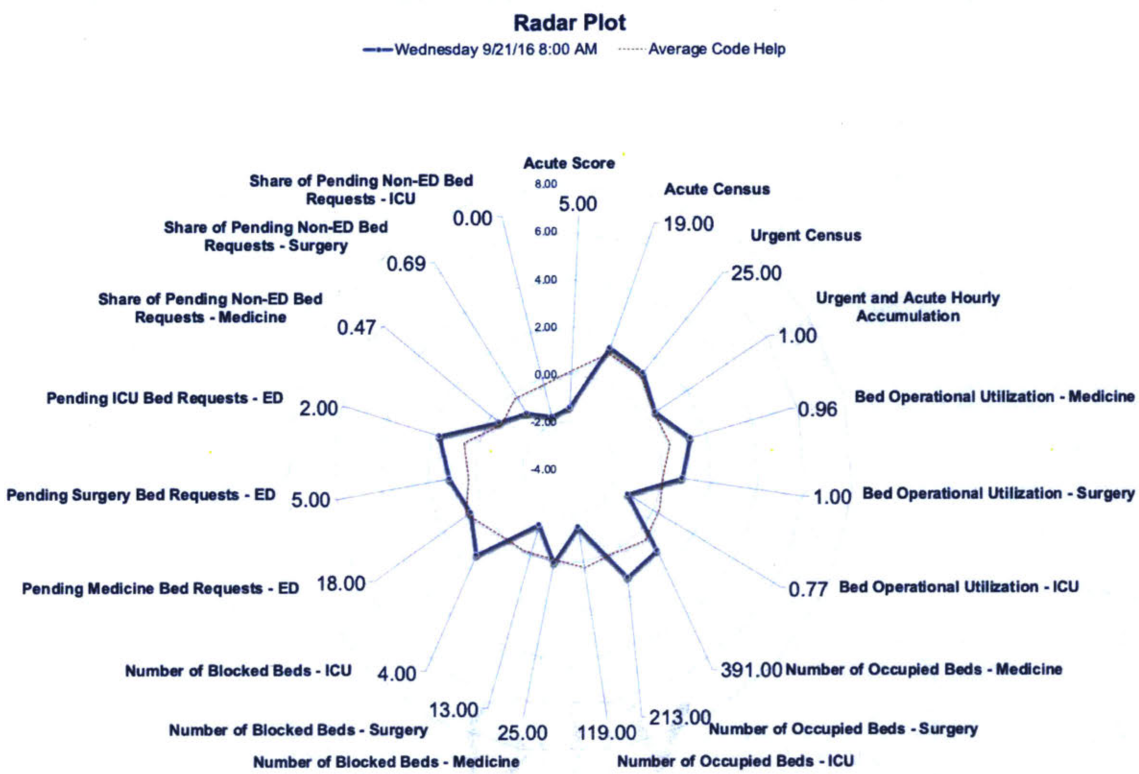

Figure 4-13: Code Help Dashboard – Example 2

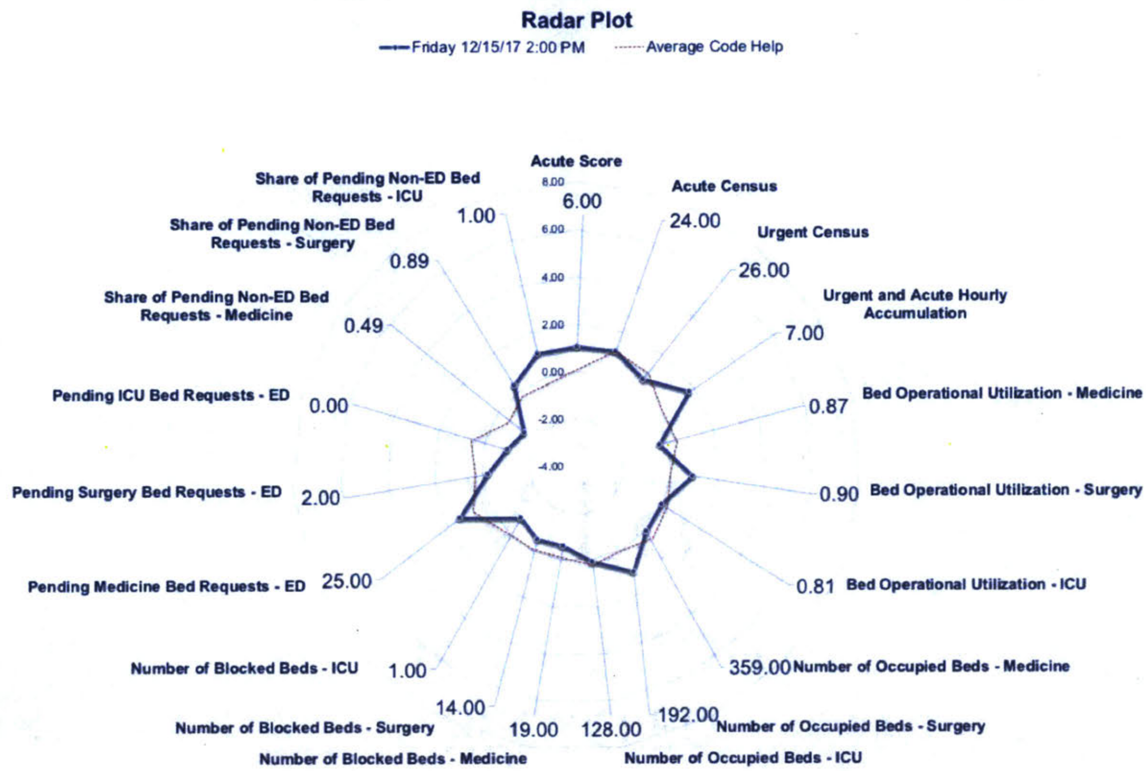

Figure 4-14: Code Help Dashboard – Example 3

The congestion dashboards depicted in Figures 4-12, 4-13, and 4-14 show two closed polygons. The blue polygon traces out the features of a *Code Help* observation, allowing the reader to observe values for these features in absolute and relative[10] terms. This dashboard also gives the reader an intuitive feel for the severity of the *Code Help* situation. As a general rule, the larger the area enclosed by the polygon, the more severe the event. Additionally, this dashboard allows the reader to compare a particular *Code Help* observation to the 'average' *Code Help*, depicted in red. In sum, this dashboard will allow ED decision-makers access to hospital-wide information that can be used to better understand the drivers of congestion during *Code Help* huddles.'

Figure 4-12 indicates that there is an exceedingly high number of ICU beds that are blocked when *Code Help* is called in Example 1. This might be a cause for concern

[10]Normalized by day-of-week and time-of-day using the method described in 4.2.1

and could possibly be a reason for delaying ED patients with bed requests on ICU floors.

Figure 4-13 indicates that both Medicine and Surgical floors are almost entirely full at the time *Code Help* is called in Example 2. This is likely the reason behind ED congestion on that particular occurrence of *Code Help*.

Figure 4-14 indicates a high patient accumulation – 2 standard deviations above expectation for that specific day-of-week and time of day – in the Urgent and Acute pods in the hour leading up to the *Code Help* alarm. This is the most likely reason for congestion in this case.

Chapter 5

Early Indicators of Discharge

In Chapter 4, we identified high operational utilization on Medicine floors to be a key driver for *Code Help*. As such, expediting the discharge process of patients who are medically ready for discharge is a critical operational response to relieve ED congestion. One key hurdle that stands in the way of this process is the inability to identify patients who are ready to be discharged in a consistent manner using data from the *Epic* system. In this chapter, we identify operational metrics indicating that a patient is in the process of being discharged and analyze the distribution of lead times these metrics provide. The end-goal of this analysis is to identify the metrics that can be leveraged to effectively generate a short-list of patients to focus on expediting through discharge when *Code Help* is activated.

5.1 Early Indicators of Discharge

We explore four operational indicators for the purposes of our analysis:

1. **Discharge Summaries:** Letter written by physician containing important information about a patient's hospital visit. These summaries contain information such as reason for hospitalization, lab results, a description of the treatment process, changes to medication, and follow-up information. These summaries are usually written on the last day of hospitalization prior to discharge. In some cases, however, they are written after the patient has already left the hospital.

2. **Discharge Orders:** Order that is written by a physician indicating that their patient is ready for discharge. This is usually the last order that is filed during a hospital stay.

3. **Outpatient Pharmacy Orders:** Medication order that is put in by physician and routed to an off-campus pharmacy.

4. ***Epic* Definite Discharge Flag:** Button in *Epic* that nurses use to indicate that a patient is medically ready for discharge. During *Code Help* meetings, the number of patients that are "Definite Discharge" is quoted to help assess the acuity of the situation. According to policy, the "Definite Discharge" flag is meant to give a lead time of at least one hour to discharge.

5.1.1 Discharge Summaries

We join the *ProcedureMGH* table to the *PatientEncounterMGH* table in the *EDW* database and select the discharge timestamp and the timestamp indicating the filing of a discharge summary for all inpatients[1](133,634 observations) between June 2016 and July 2018.

[1]on the following floors: MGH Bigelow 11 Med, MGH Bigelow 6 PICU, MGH Ellison 18 Pedi, MGH Ellison 17 Pedi, MGH White 10 Medicine, MGH White 11 Medicine, MGH Blake 11 Psych, MGH Bigelow 9 Med, MGH Lunder 10 Oncology, MGH White 8 Medicine, MGH White 9 Medicine, MGH Ellison 10 Stp Down, MGH Bigelow 13 RACU, MGH Lunder 9 Oncology, MGH Blake 7 MICU, MGH Blake 12 ICU, MGH Lunder 6 Neuro ICU, MGH Bigelow 14 Vasc, MGH Lunder 7 Neuro, MGH Ellison 12 Med, MGH Phillips 20 Med, MGH Ellison 16 Med, MGH Ellison 4 SICU, MGH White 7 Gen Surg, MGH Phillips 22 S/M/O, MGH Blake 6 Transplant, MGH Blake 8 Card SICU, MGH Phillips 21 Gyn, MGH Ellison 14 Brn ICU, MGH Ellison 14 Plastcs, MGH Ellison 13a Ob-Ante, MGH Blake 13 Ob, MGH Ellison 13o Ob-Post

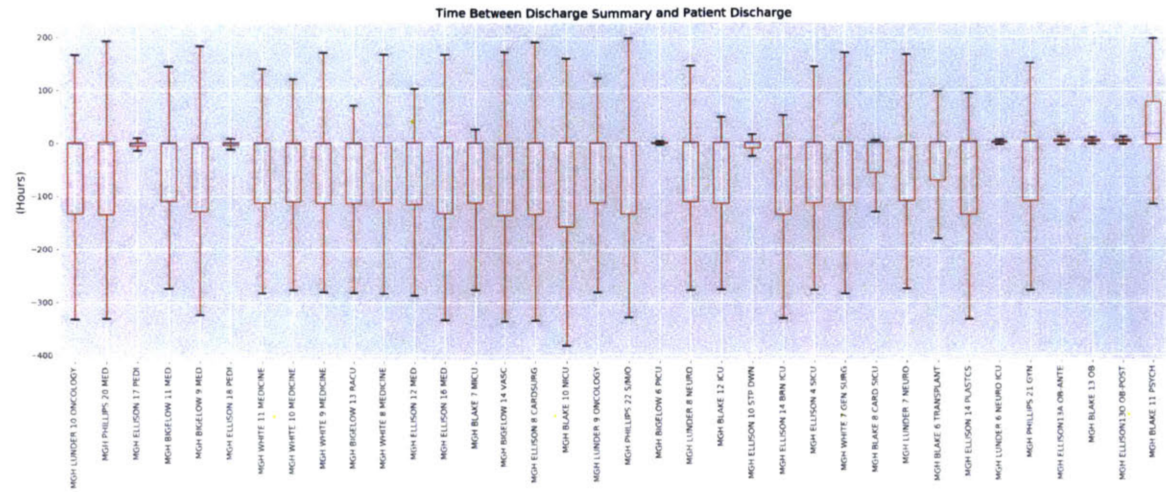

Figure 5-1: Distribution of Time Between Discharge Summary and Patient Discharge by Floor.

Figure 5-1 shows a boxplot of the time delta between the filing of a discharge summary and patient discharge, where a negative delta indicates that the discharge summary was filed post discharge. This figure highlights two shortcomings of discharge summaries as it pertains to using them as an early indicator of discharge. First, the large variance in the distribution for most floors manifested in an interquartile range (IQR) of up 150 hours on some floors. Additionally, discharge summaries seem to be filed after discharge in most cases and as such, they do not provide a reliable indicator for discharge for a large patient population.

5.1.2 Discharge Orders

Similarly, we join the *ProcedureMGH* table to the *PatientEncounterMGH* table in the *EDW* database and select the discharge timestamp and the timestamp indicating the filing of a discharge order for all inpatients (133,634 observations) between June 2016 and July 2018.

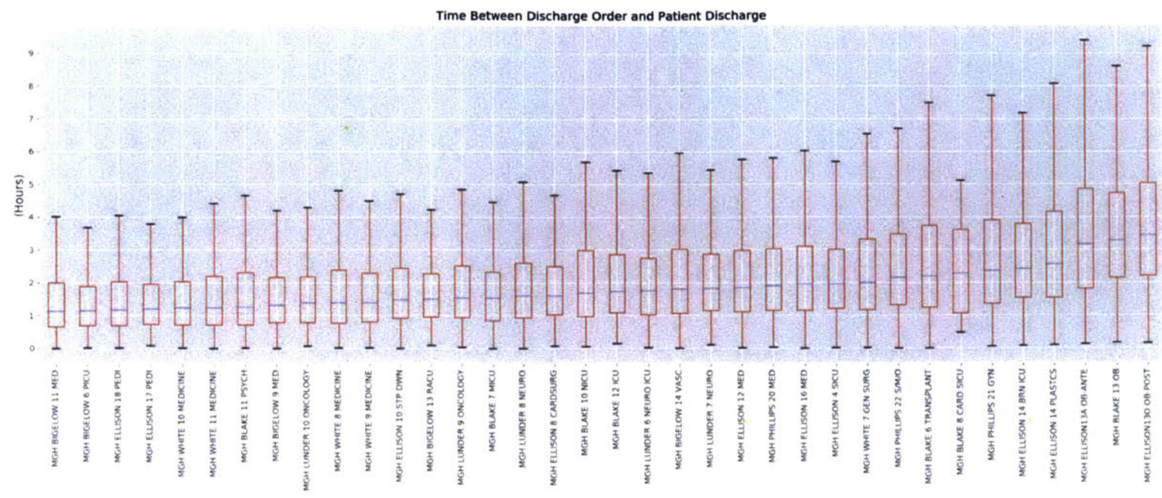

Figure 5-2: Distribution of Time Between Discharge Orders and Patient Discharge by Floor.

Figure 5-2 shows a boxplot of the time delta between the filing of a discharge orders and patient discharge. Discharge orders provide a median lead time ranging between 1 hour with an IQR of 1.5 hours for MGH Bigelow 11 Med and a median of 3.5 hours with an IQR of 3 hours for MGH Ellison 13o Ob-Post. Given the reasonably low variance in the distribution of lead times, discharge orders are, as expected, considered effective indicators of imminent discharge.

5.1.3 Outpatient Pharmacy Orders

We join the *PatientEncounterMGH* table to the *MedicationMGH* table and the *Pharmacy* table in the *EDW* database and select the discharge timestamp and the timestamp indicating the filing of a pharmacy order from an outpatient pharmacy (23,491 observations) for all inpatients between June 2016 and July 2018. This makes up 17.58% of all inpatients seen within this period.

Table 5.1: Comparison Between Lead Time of Discharge Orders and Pharmacy Orders

	Observations	% of Total
Pharmacy Order LT >Discharge Order LT	6,965	29.65%
Pharmacy Order LT = Discharge Order LT	13,825	58.85%
Pharmacy Order LT <Discharge Order LT	2,701	11.50%
Total Observations	23,491	100%

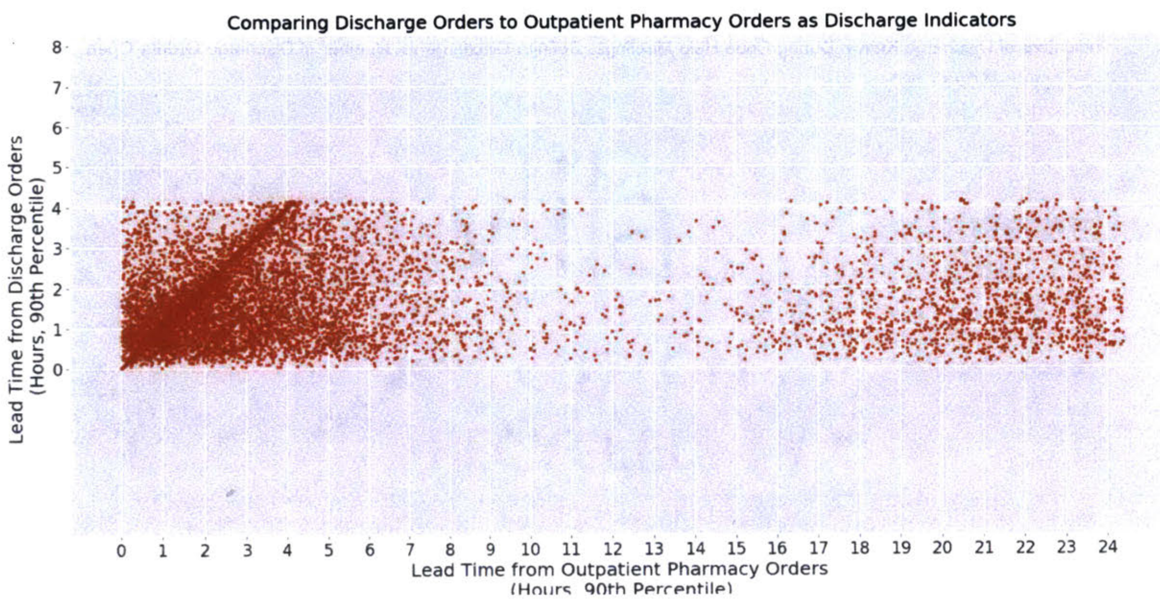

Figure 5-3: Scatter Plot of Discharge Order Lead Time vs. Pharmacy Order Lead Time

Table 5.1 indicates that for 88.50% of patients with outpatient pharmacy orders, using the timestamp of the filing of the outpatient pharmacy order as an early indicator of discharge does at least as well as using the discharge order timestamp. In 29.65% of the cases, using the pharmacy order timestamp allows more lead time.

5.1.4 *Epic* Definite Discharge Flag

We generate a vector of the number of inpatients with a definite discharge flag from *Code Help* reports belonging to all *Code Help* meetings running between 4/8/16 and

8/6/18. We compare it with the actual number of patients discharged within 1 hour, 2 hours, and 3 hours of the meeting and report a mean-squared error (MSE) measure. We proceed similarly to calculate a mean-squared error measure using discharge orders as an indicator of discharge and report the results in figure 5-4 below.

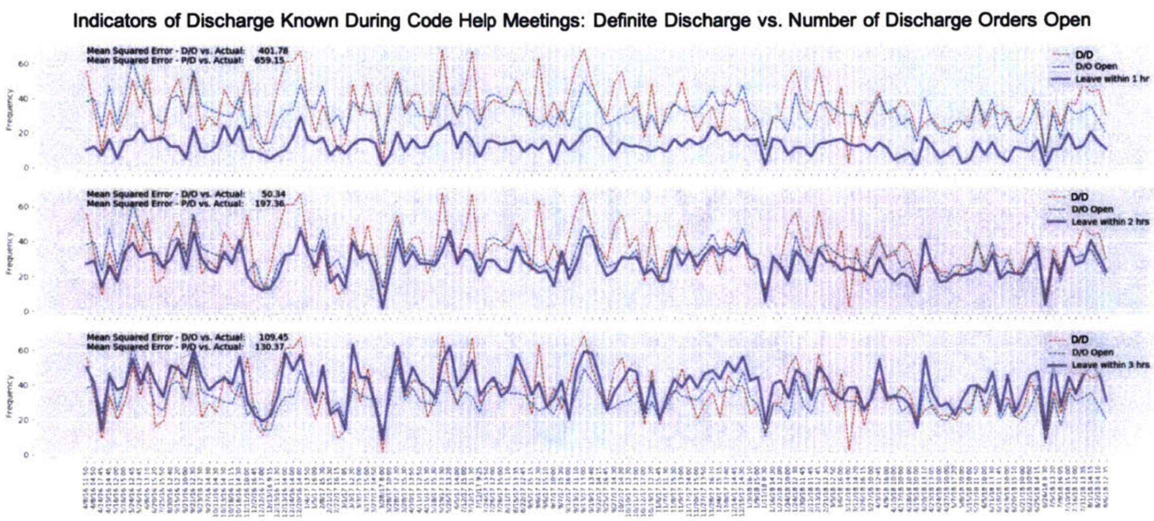

Figure 5-4: MSE of Definite Discharge Flag vs. MSE of Discharge Orders for a Lead Time of 1 Hour, 2 Hours, and 3 Hours

Figure 5-4 indicates that the process of examining discharge order timestamps fares better than considering the definite discharge flag when attempting to identify patients who are in the process of being discharged.

5.2 Potential Impact and Limitations

5.2.1 Potential Impact

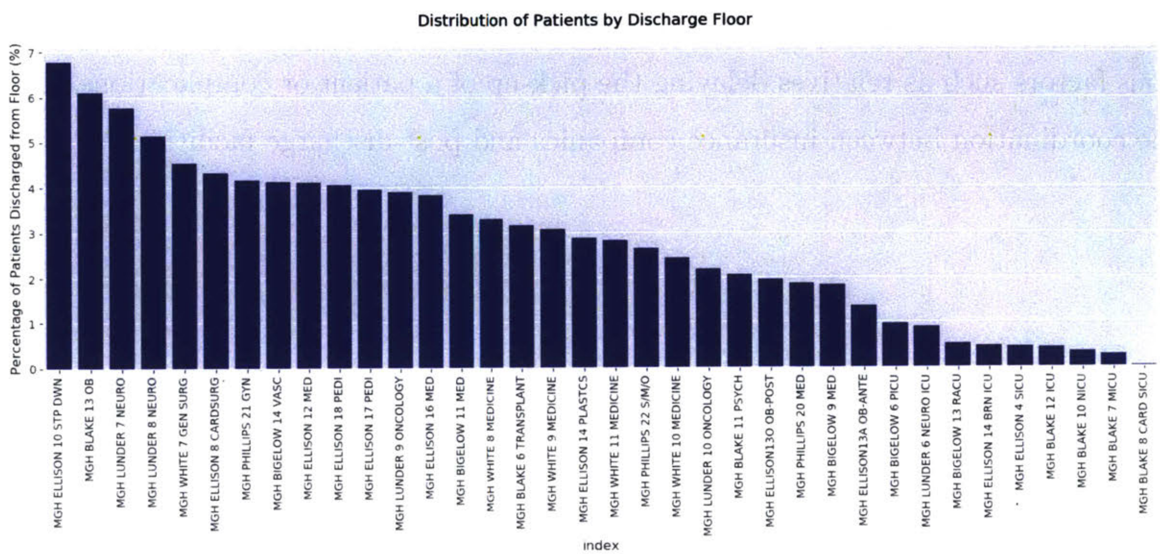

Figure 5-5: Distribution of Patients Discharged by Floor

Figure 5-2 suggests that the floors in the top decile in terms of lead time between discharge order and patient discharge are *MGH Ellison 13A OB-Ante*, *MGH Blake 13 OB*, and *MGH Ellison 13O OB-Post*. As can be seen from Figure 5-5, these floors represent about 9.3% of Medicine patients at MGH, corresponding to a number between 4,000 and 5,000 patients. Decreasing the median lead time between discharge order and patient discharge on these floors from the current values to match the hospital-wide figure of 1.7 hours will free up roughly 6,800 bed-hours of capacity per year. Further, if MGH were able to bring down the lead time of all floors that are currently in the upper 50th percentile to the value of the median, it would be able to free up 13,802 hours of capacity per year, corresponding to about 0.2% of its total Medicine bed capacity.

5.2.2 Limitations: Barriers to Timely Discharge

The acceleration of patient discharge has many limitations that are important to consider. A few barriers that surfaced from interviews with hospitalist provider teams at MGH included the lack of patient readiness, facility placement, and transportation. While some of these issues can be readily addressed with proper planning and the streamlining and standardization of the discharge process, others depend on exogenous factors such as relatives delaying the pick-up of a patient or complications with the coordination between insurance companies and post-discharge facilities.

Chapter 6

Code Help Prediction

In this chapter, we attempt to build a model that will allow us to predict, at 7 AM in the morning on a given day, whether *Code Help* will occur at any point between 7 AM and 11 PM. We leverage daily observations running between 06/01/2016 and 12/31/2017 and select the appropriate features and model type and hyper-parameters to achieve the best predictive performance.

6.1 Model Choice

Since our dataset is rather small (400 observations), we chose to employ logistic regression with L_1 and L_2 regularization in order to avoid overfitting. Other models were attempted (e.g., Support Vector Machines, Classification and Regression Trees, Random Forest, Multi-layer Perceptrons) but they all yielded significantly inferior results and were discarded from consideration.

6.1.1 Logistic Regression

The logistic regression is a regression analysis where the independent variable is binary. Dependent variables can be either discrete or continuous. The main components of a logistic regression are [30]:

Random Component. The probability distribution of the dependent variable is

Binomial.

$$Y_i \sim Binomial(n_i, \pi_i)$$

Where n_i is the binomial denominator and π_i is the probability.

Systematic Component. The linear combination of the dependent variables.

$$\eta_i = x_i^T \beta$$

Where x_i is the vector of dependent variables for observation i and β is the vector of regressors.

Link Function. The logit function is the link function.

$$\eta_i = logit(\pi) = \log \frac{\pi}{1-\pi} = \sum_{j=0}^{p} \beta_j x^{(j)}$$

6.1.2 LASSO and Ridge Logistic Regressions

The logistic regression model has the following log-likelihood [30]:

$$-\sum_{i=1}^{n} \log(\Pr_{\beta}(Y_i \mid X_i)) = \sum_{i=1}^{n} \{-Y_i \sum_{j=0}^{p} \beta_j x^{(j)} + \log(1 + \exp \sum_{j=0}^{p} \beta_j x^{(j)})\}$$

Where n is the total number of observations, p the total number of features. Written in terms of the loss function ρ, we get:

$$\rho_\beta(x, y) = -y \sum_{j=0}^{p} \beta_j x^{(j)} + \log(1 + \exp \sum_{j=0}^{p} \beta_j x^{(j)})$$

The LASSO and Ridge estimators for logistic regressions are:

$$\hat{\beta}_{LASSO}(\lambda) = \underset{\beta}{\operatorname{argmin}}(n^{-1} \sum_{i=1}^{n} \rho_\beta(X_i, Y_i) + \lambda \|\beta\|_1)$$

$$\hat{\beta}_{Ridge}(\lambda) = \underset{\beta}{\operatorname{argmin}}(n^{-1} \sum_{i=1}^{n} \rho_\beta(X_i, Y_i) + \lambda \|\beta\|_2)$$

6.1.3 Analysis Method

The general analysis conducted is as follows:

1. Join *ED Census*, *CDU Census*, *Number of Medicine Boarders*[1].

2. Apply scaling as described in section 3.2.1 to get relative values with regards to time of day and day-of-week.

3. Shuffle the observations randomly.

4. Split the observations into 70% training, 30% testing.

5. Upsample positive classes (*Code Help*) in the training set by drawing with replacement to reach class balance.

6. For each model type, build regression model from the training data and perform regularization hyper-parameter cross validation.

7. Generate predictions on the testing set and calculate the area under the receiving operator characteristic curve (AUROC) and the following performance measures:

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

8. Repeat steps 3 through 6 one thousand times and record the distribution of all regressors, precision values, recall values, and AUROC values.

9. Determine an empirical confidence interval for every regressor based on a p-value of 0.05 and flag regressors as significant or not significant.

By repeating the data split several times, confidence grows in the mean AUROC, Precision, and Recall values, as well as in the statistically significant regressors. Due to the randomness of the training and testing split, some features may show up as

[1] Boarders waiting for a bed on a Medicine floor

significant in some of the model runs, but only the truly significant ones will be selected nearly always.

6.1.4 Modeling Performance

LASSO Model

Table 6.1: Modeling Performance Measures for LASSO Model

Metric	5^{th} **perc.**	25^{th} **perc.**	**Median**	75^{th} **perc.**	**Max**
Precision	0.29	0.32	0.35	0.38	0.49
Recall	0.59	0.68	0.73	0.77	1.0
AUROC	0.63	0.68	0.71	0.74	0.84

Table 6.2: Regularization Parameter for LASSO Model

λ	**Number of Times Selected (out of** $1,000$**)**
0.1	542
1	234
10	224
100	0
1000	0

Table 6.3: Regressor Means and Significance for LASSO Model

Feature	**Regressor**	**Mean Value**	**Statistically Significant**
ED Census at 7 AM	β_1	0.768869	Yes
CDU Census at 7 AM	β_2	0.485556	Yes
Number of Medicine Boarders at 7 AM	β_3	0.133990	No

Ridge Model

Table 6.4: Modeling Performance Measures for Ridge Model

Metric	5^{th} **perc.**	25^{th} **perc.**	**Median**	75^{th} **perc.**	**Max**
Precision	0.29	0.33	0.35	0.38	0.53
Recall	0.59	0.68	0.77	0.82	1.0
AUROC	0.64	0.69	0.72	0.75	0.85

Table 6.5: Regularization Parameter for Ridge Model

λ	**Number of Times Selected (out of** $1,000$**)**
0.1	71
1	66
10	103
100	678
1000	82

Table 6.6: Regressor Means and Significance for Ridge Model

Feature	**Regressor**	**Mean Value**	**Statistically Significant**
ED Census at 7 AM	β_1	0.431944	Yes
CDU Census at 7 AM	β_2	0.340299	Yes
Number of Medicine Boarders at 7 AM	β_3	0.207697	No

6.1.5 Discussion of Results

The modeling results indicate that LASSO and Ridge have very similar performance parameters and have selected the same two statistically significant features. These models exhibit a higher degree of sensitivity than positive predictive value. This means that they will only miss, on median, about 20% of the *Code Help* days when predicting at 7 AM in the morning. Their relatively low positive predictive value can be attributed to interventions that occur after 7 AM that lead to the mitigation of would-be *Code Help* days. Given all this, it is wise to leverage the predictions of these models as precocious alarms to start freeing up capacity on Medicine floors as early as possible.

Chapter 7

Code Help Mitigation Measures

Based on the results of this work and discussions with ED administrators, ED clinicians, inpatient providers, nurses, and hospitalists, we have identified a list of measures that will mitigate the problem of frequent *Code Help* alarms and the overall ineffective response to congestion events at the MGH ED. We will split our recommendations along three time horizons: the short-term, medium-term, and long-term.

7.0.1 Short Term

Short-term quick-wins that can be implemented immediately include involving Admitting in the Code Huddle. Currently, the *Code Help* decision makers only rely on their knowledge of the state of the ED when deciding whether or not to call *Code Help.* Adding Admitting to the huddle will provide them with transparency into the state of the entire hospital when it comes to scheduled admissions and discharges, which will in turn result in a lower incidence of *Code Help* events of type 2 that are driven by a high volume of ED arrivals and a lower volume for operational capacity utilization of medicine beds. Currently, inpatient providers find it difficult to expedite the discharge process for their patients, even those who are close to becoming medically ready for discharge. Using early discharge indicators such as Outpatient Pharmacy Orders for patients that have them and Discharge Orders will allow us to generate a list of priority patients that providers can focus on discharging whenever

Code Help strikes.

7.0.2 Medium Term

Medium term solutions include revisiting the *Code Help* definition itself to include a component related to inpatient operational capacity utilization. As such, the decision of whether or not to call *Code Help* will take into account not only the current state of the ED, but also the state of the inpatient floors. An ED that is backed-up while inpatient floors are underutilized is not as concerning as busy ED when inpatient floors are full. Additionally, a full-scale discharge prediction model can be developed and leveraged to prioritize patients according to their readiness for discharge using a vector of operational and clinical features.

7.0.3 Long Term

Long term solutions include developing a real-time *Epic* dashboard to inform decision makers of the state of the hospital during the *Code Help* huddle. Additionally, it is important to build out ED capacity where possible, especially in the Clinical Decision Unit (CDU) that is often found to be the bottleneck in the ED care process.

Chapter 8

Conclusions and Future Work

8.1 Conclusions

Our exploratory feature analysis of *Code Help* uncovered several important insights. First, we found that *Approaching Code Help* alarms that eventually convert to *Code Help* generally occur earlier in the day than those that don't. The converting *Approaching Code Help* alarms exhibit a peak in probability density at around noon-time, whereas *Approaching Code Help* alarms that do not convert exhibit a peak in probability density around 1:30 PM, with the probability density of *Code Help* incidence peaking at around 1:00 PM. Since *Code Help* is largely a hospital capacity problem, accelerating discharges towards the afternoon generally relieve ED congestion. Additionally, we found that 80% of *Approaching Code Help* alarms that end up converting to *Code Help* do so within 3 hours of activation and that 90% of *Approaching Code Help* alarms that convert occur before 3 PM. Also, whenever *Code Help* is activated, the trigger goes out within two hours of reaching objective criteria. Moreover, we found that *Code Help* objective criteria are reached with similar frequency regardless of the day of the week but that reaching objective criteria is most likely to convert to *Code Help* on Mondays and Tuesdays, less likely on Wednesdays and Fridays, and least likely on Thursdays. This is likely driven by day-of-week patterns of inpatient bed operational capacity utilization. Our classification work has found most *Code Help* events to be driven by inpatient congestion, with a smaller class of *Code Help* events that are driven by a surge in ED arrivals. Lack of transparency into the overall state of the hospital during *Code Help* huddles generates unnecessary alarms, especially in the cases where inpatient bed operational capacity utilization is relatively low. Our prediction work has allowed us to flag high likelihood days for *Code Help* at 7 AM in the morning by looking at *ED Census*, *CDU Census*, and *Number of Medicine Boarders*, capturing 77% of all positive examples. While this has not been verified, the low precision of our model (35%) can be attributed to effective responses to congestion on would-be *Code Help* days. We identified Discharge Orders as early indicators for discharge, providing 1-to-3 hours of lead time before discharge, on median. Pharmacy Orders perform better for 88.5% of the patient population that has them, which makes up 17.58% of the total inpatient population. These indicators can be leveraged by providers to help prioritize patients by their readiness for discharge so that they can focus on patients that are closest to discharge when *Code Help* strikes. Short-term quick-wins that can be implemented immediately include involving Admitting in the Code Huddle, which is expected to result in a lower incidence of *Code Help* events of type 2 that are driven by a high volume of ED arrivals and a lower volume for operational capacity utilization of medicine beds. Medium term solutions include revisiting the *Code Help* definition itself to include a component related to inpatient operational capacity utilization. As such, the decision of whether or not to call *Code Help* will take into account not only the current state of the ED, but also the state of the inpatient floors. A full-scale discharge prediction model can be developed and leveraged to prioritize patients according to their readiness for discharge. Long term solutions include developing a real-time *Epic* dashboard to inform decision makers of the state of the hospital during the *Code Help* huddle. Additionally, it is important to build out ED capacity where possible, especially in the Clinical Decision Unit (CDU) that is often the bottleneck in the ED care process.

8.2 Future Work

8.2.1 Discharge Prediction

Future work includes integrating discharge prediction models for Medicine and Surgery patients into the *Code Help* response protocol. These models can provide a priority list of patients who are closest to discharge so that their dispatch can be expedited during capacity alarms. Two types of models are currently being explored: the first relying on operational and clinical features tied to each patient's care path, and the second utilizing natural language processing techniques on Case Management notes to predict which patients were likely to be ready for discharge then next day.

8.2.2 Revisiting *Code Help* Criteria

Additionally, it is important to revisit *Code Help* criteria to include a measure of bed operational capacity utilization of Medicine floors as a factor. *Code Help*, as we have determined, is largely a downstream congestion problem and neglecting the state of the inpatient floors when deciding whether or not to call it can result in unnecessary alarms.

8.2.3 ED Census Prediction

Many research groups have managed to predict ED census on a given day using regression and time-series analysis techniques. A prediction tool for ED census might prove helpful in directing more effective workforce scheduling and assignment within the ED.

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Appendix A

Capacity Alarm Paging Team

Below is a list of ED Leadership staff and affiliated departments and personnel paged when *Approaching Code Help*, *Code Help*, and *Capacity Disaster* levels are reached in the MGH ED:

- Acute Psychiatric Service Director
- Associate Chief Nurses
- Case Management Leaders
- ED Leadership Team
- ED Resource Nurse
- ED Charge Coordinator
- ED Acute Attending
- ED Acute Attending MD
- Emergency Medicine Residents
- Emergency Imaging
- Intensive Care Unit (ICU) Leaders / Critical Care Team
- Infection Control

- Materials Management Director
- Medical Chief Resident
- Medical Senior Resident
- Medical Team 4 Supervisor
- Neurology Service: Consult and Senior Residents
- Operating Room (OR) Staff Admin on Call
- Patient Care Services (PCS) Clinical Nurse Specialists
- PCS Executive Team
- PCS Inpatient Resource Nurses
- PCS Nursing Directors
- PCS Nursing Supervisors
- PCS Operations Managers
- Senior Vice Presidents
- Service-based Inpatient Access Nurses
- Social Services Director
- Emergency Surgery Attending Physician
- Surgical Senior Resident in ED
- Trauma Administrative Director
- Trauma Nurse Director

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