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Engineering Inpatient Discharges: Disposition Prediction and Day-of-Discharge Planning

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ENGINEERING INPATIENT DISCHARGES: DISPOSITION PREDICTION AND DAY-OF-DISCHARGE PLANNING

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy

By

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I HEREBY RECOMMEND THAT THE DISSERTATION PREPARED UNDER MY SUPERVISION BY Nicholas Ballester ENTITLED Engineering Inpatient Discharges: Disposition Prediction and Day-of-Discharge Planning BE ACCEPTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF Doctor of Philosophy.

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ABSTRACT

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Inpatient discharge planning is a critical decision point in patient care, with implications for the efficiency of the inpatient unit as well as other units of the acute care hospital. Inefficient discharge planning can cause patient boarding (waiting for beds) in the upstream units. While this is a poignant and well-known problem in healthcare, very little quantitative research exists that proposes approaches to alleviate it. To address this issue, we apply Systems Engineering methods with focus on three key challenges in inpatient discharge planning.

First, to aid inpatient care providers in predicting discharge disposition (home vs. non-home) within 24-hours of a patient being admitted, we develop an early-warning prediction tool. This tool is derived from a multivariable logistic regression model built using data from a general medicine unit at a VA hospital. The tool is expected to aid the inpatient staff in proactively classifying non-home discharges from home in an effort to initiate early discharge planning and avoid non-medically related discharge delays.

Second, to improve hospital bed flow and reduce upstream patient boarding, we propose a novel discharge target strategy, *n*-by-*T*, for an inpatient unit's planning of daily discharges. A stochastic simulation model developed in collaboration with a trauma unit at a local hospital predicted that this strategy could offer significant advancement in

discharge completion time and reduction in upstream boarding; these findings were later validated via a pilot at the unit. Consistent findings via an extension to a neurology unit at another hospital suggest potential generalizability of this strategy.

Third, to assist ancillary service providers on inpatient units in sequencing their daily patient workflow, we propose a novel approach to construct implementable and robust strategies. We develop a scenario-specific mixed-integer programming model to derive optimal sequences that minimize average upstream patient boarding under due-date constraints. We then design a simulated annealing based metaheuristic to derive a single sequencing strategy that is promising across all scenario-specific optimal sequences for a given system configuration. An experimental evaluation of our approach suggests that our proposed strategies outperform several realistic strategies on boarding time.

In summary, our research proposes easy-to-understand and implementable strategies derived from optimization and data analytics based methodologies to aid effective and efficient planning of discharges and improve patient flow through the hospital.

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Acknowledgement

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1 INTRODUCTION

1.1 The US Healthcare Continuum

The United States spares no expense when it comes to healthcare. In 2014, healthcare spending totaled $3 trillion, or 17.5% of the GDP (CDC, 2016). Yet, despite this extraordinary cost, the U.S. has consistently ranked behind other developed countries in healthcare system quality. In the same year, the U.S. ranked last among 11 nations in healthcare system efficiency, equity, and support for healthy living, while ranking 9th in healthcare system access and 5th in quality of care, coming in last overall, even though it had the highest healthcare spending per capita (Davis et al., 2014). Clearly, there is much room for improvement.

Healthcare encompasses a broad continuum, including home health care, acute care (outpatient and inpatient), long-term care, and others (Figure 1-1). Each stage in the continuum provides a different level of care, corresponding to different stages in the human life cycle, and a typical person may transition from one to another multiple times throughout his life. Thus, each facet of healthcare faces unique challenges and associated areas for potential improvement, both clinical and logistical, while the efficient coordination of care between them poses another set of challenges.

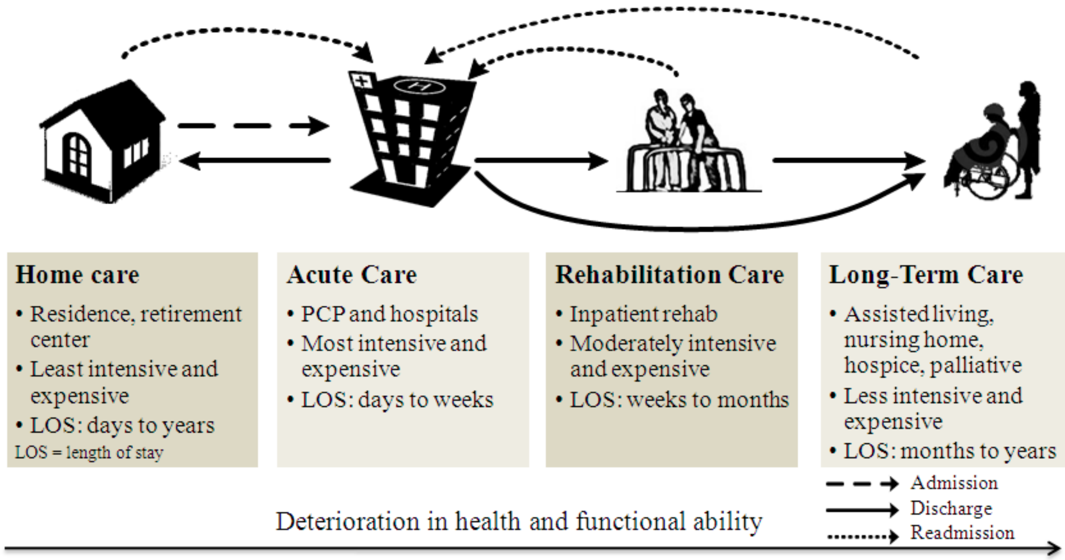


Figure 1-1: The U.S. Care Continuum

Among the various elements of the healthcare continuum, acute care hospitals (ACH) are the most expensive and the most utilized, with hospital care accounting for 32.1% of U.S. national health expenditures in 2014 (CDC, 2016). ACHs provide a vast array of services to patients with highly variable needs and preferences. These services are delivered by a set of functional units, such as emergency departments (ED), laboratory and diagnostic facilities, perioperative systems, intensive care units (ICU), post-anesthesia care units (PACU), inpatient medical/surgical units (IU), and so forth. Patients coming to an ACH must be navigated through many, if not all, of these differing functional units to receive the service they need during an episode of care; they also arrive in multiple different ways, such as walk-ins, ambulance, scheduled (elective), or transfers from other hospitals (Figure 1-2). For example, a patient (referred to as he for ease of exposition) injured in a car accident may arrive via ambulance to the ED, where, in addition to the ED physicians and nurses, he may require the services of the medical imaging department; after being triaged in the ED, he may be sent to surgery, after which he may be admitted to an inpatient ward for care and rehabilitation over the course of several days before being discharged to home with home health therapy services (a nurse therapist visiting him at home regularly for the next week).

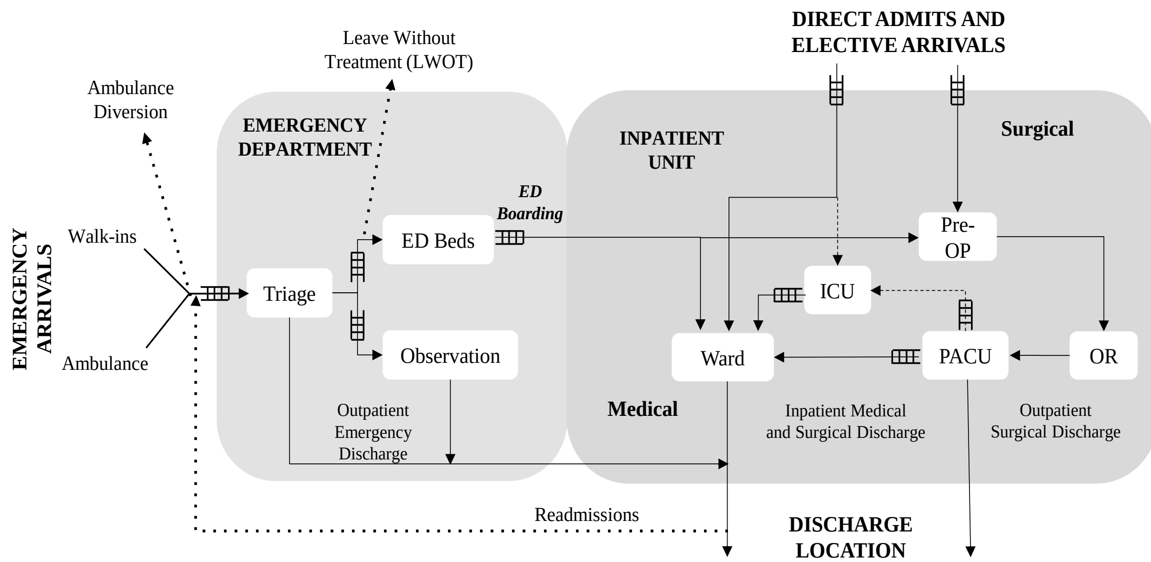


Figure 1-2: Example Patient Pathways at an ACH

Patient care at an ACH can be grouped into two major categories: emergency care, provided in the emergency department (ED), and inpatient care, provided in inpatient units (IU). EDs and IUs operate independently of one another for the most part, the critical exception being that EDs can (and often do) send their patients on to IUs for further care (referred to as hospital admissions). This is the crucial link between the two, with EDs accounting for over half of inpatient admissions in the U.S. by 2009 (Morganti et al., 2013).

The IU plays a vital role in acute patient care; it is the heart of an ACH. This is where patients with acute conditions, medical and surgical, are cared for over days and weeks until the patient is clinically ready to resume normal life directly or indirectly via rehab. The IU receives patients from multiple sources, some of which are within that

ACH; e.g., ED patients with conditions requiring more than 24 hours of care are admitted into the IU, and perioperative suites perform surgeries, after which patients are transferred to the IU (via PACU) for recovery and monitoring. Other sources of patient admissions to an IU are external, such as elective patients with scheduled admissions directly to the IU and patients directly transferred into the IU from other hospitals. The IU is supported by various ancillary units such as laboratories, imaging suites, in-house therapy departments, social work, and the environmental and transportation services. These units provide specialized staff such as physical therapists, occupational therapists, and social workers to assist the physicians and nurses with patient care in the IU.

The IU, in a sense, *is* the hospital proper. Inefficiencies here reverberate back to the rest of the ACH, especially the ED in terms of ED boarding and crowding (Powell et al., 2012; Wong et al., 2010; M. Vermeulen et al., 2009), and from the ACH they spread to the rest of the healthcare continuum. Given this central role IUs play in the entire healthcare system, we now focus on the key decisions involved in IU planning and operation.

1.2 Decisions Related to IU Operations

To understand the IU operations, consider a typical inpatient hospital stay. From admission to discharge, there are a myriad of potential decision points, each with its associated objectives, constraints, vested parties, and subsequent impact upon both patient care and overall system efficiency.

Figure 1-3 illustrates some of the most important decision-making areas during a typical inpatient hospitalization. These focus areas can be grouped into three basic categories by their location within the timeline of the hospitalization—upon patient admission or shortly thereafter, throughout the duration of the patient treatment, and on the day of discharge or within a few days prior. We now discuss each of these briefly.

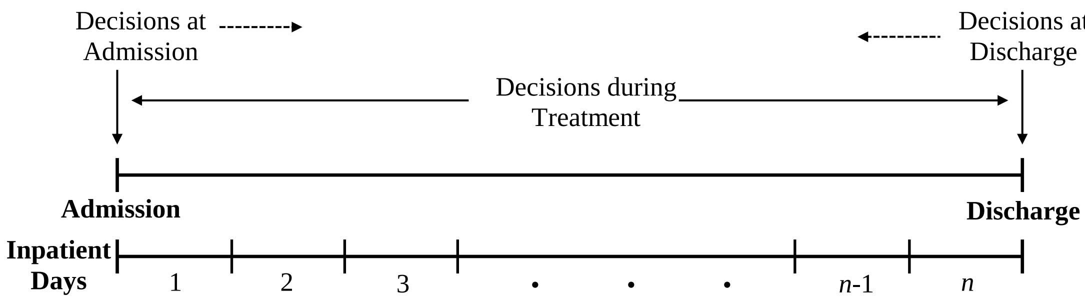


Figure 1-3: Decision Points during an Inpatient Stay

1.2.1 At Admission

The following are a few key decisions during the admission of a patient to an IU:

- Bed Capacity/Allocation: From a patient care perspective, the patients must be assigned the most appropriate resources corresponding to their condition, as well as a location amenable to their comfort (e.g., shared vs private room, windows, aesthetics, space to accommodate family/visitors). From a hospital logistics standpoint, patients must be assigned to inpatient beds as quickly as possible to reduce ED boarding and crowding, while still attempting to meet patient needs. In a broader sense, the hospital must also determine how to allocate bed capacity to each service based on multiple factors such as predicted arrival rates, average length of stay, and target unit occupancy rate. Several analytical studies have examined these questions, usually with simulation or queueing theory (Green, 2004; Harper & Shahani, 2002).
- Care Team Formulation: Unfortunately there is often a tradeoff between the care providers most qualified to care for the patient and the care providers who have

capacity to spare. This problem is particularly poignant for nurses. Balancing nurse workload can have serious impacts on patient safety; nurse staffing levels and patient assignments are important questions for units to consider (Penoyer, 2010; Caryon & Gurses, 2008). Both simulation and mathematical optimization studies exist on this topic (Sundaramoorthi et al., 2009; Punnakitikashem, 2008).

- <u>Patient Outcomes Prediction</u>: Either upon admission or shortly thereafter, units wish to know what to expect with regards to the patient's needs, so that they can plan ahead and pre-allocate the necessary resources. Prevention of negative clinical patient outcomes is also a top priority. Some of the most commonly targeted areas for predictive model development include: patient mortality (Lee et al., 2003), length of stay (Paterson et al., 2006), hospital cost (Evers et al., 2002), and discharge disposition (Beaulieu et al., 2014).

1.2.2 During Treatment

Some of the key decisions while the patient is being treated in the IU include the following:

- <u>Length of Stay (LOS) Reduction</u>: This has always been the most important and challenging topic for hospitals, from both an administrative and a clinical perspective. Due to the fact that Medicare and Medicaid reimbursements to hospitals are based on geometric length of stay (GLOS), hospitals have an incentive to not exceed the established GLOS. Additionally, reducing length of stay can reduce the risk of hospital-based adverse patient outcomes, such as hospital-acquired infections; however, reducing length of stay and potentially discharging a patient before they are medically ready can lead to negative patient outcomes after leaving the hospital and increased readmission risk (Bueno et al., 2010). Different approaches have been taken to address this problem (Wang et al., 2012; Lagoe et al., 2005).

- Care Team Communication Improvement: Given the diverse nature of the team caring for a patient, which consists of physicians, nurses, therapists, social workers, and others, effective communication and collaboration on the patient's course of treatment is a major challenge. Lack thereof can, and often does, result in inadvertent patient harm (Leonard et al., 2004).
- Workplace Organization/Layout: Previous studies have examined hospital layout from a standard facility layout approach (Elshafei, 1977) or with simulation-based optimization (Butler et al., 1992). Recently, lean principles are increasingly being used in hospitals to assist with everything from storage of medical instruments (Marchwinski, 2007a) to workspace organization (Marchwinski, 2004) to location of offices and exam rooms (Marchwinski, 2007b).
- Operating Room Efficiency/Turnover: A broad area of research exists on increasing the efficiency of operating suites, measured in various ways such as reducing OR turnaround times, reducing OR delays, and increasing OR throughput. Multiple approaches exist, including Lean and Six Sigma (Mason et al., 2015), process redesign interventions (Harders et al., 2006), and scheduling optimization (Cardoen et al., 2010).
- Readmission Risk Identification: Readmissions are a highly undesirable phenomenon, with negative implications for both patient quality of care and hospital costs. Multiple studies have attempted to develop methods to identify

patients who are at a high risk of readmission so that hospitals can introduce proactive interventions in the patient's care (Kansagara et al., 2011).

1.2.3 At Discharge

The following are a few key decisions associated with discharging a patient from the IU:

- Disposition Determination/Discharge Initiation: At some point before the patient is discharged, the discharge disposition (e.g. home, home with health services, long term care hospital, nursing home, rehab facility) must be identified in order to initiate the corresponding preparation. This includes insurance paperwork, coordination with any destination facilities, transportation arrangement, post-discharge care planning, and patient and family instruction. Such preparation can take days, and failure to initiate in a timely manner can result in significant discharge delays; unfortunately, this is often the case in practice.
- Day-of-Discharge Unit Target Strategies: In an effort to reduce discharge delays and mitigate upstream boarding, IUs often set targets by which all discharges on a given day should be completed; typically, 12 noon is the standard. However, this is difficult to implement in reality, and may not be appropriate for every unit. This topic has but recently come to the awareness of the world of industrial engineering/operations research (IE/OR), and only a few studies have made initial attempts to optimize it (Matis et al., 2015; Ozen et al., 2014).
- Care Provider Patient Prioritization: Clinical providers, such as doctors and nurses, and ancillary services, such as physical therapists, occupational therapists, and social workers, must attend to multiple patients every day. While some of these patients are new arrivals, others are either currently in treatment or slated for

discharge on that day. The order in which these patients are seen affects the time of discharge for the discharge-ready patients. However, prioritizing them may be difficult, given the imperative care needs of new arrivals or patients in treatment. In practice, care providers may have individual prioritization schemas to handle their daily workload, but there are no enforced, optimal strategies.

1.3 Research Focus—Inpatient Discharges

From a logistics standpoint, one of the most important events in an inpatient's care encounter is the discharge. Unnecessary discharge delays negatively impact the patients and their families (frustration, risk of hospital acquired adverse care outcomes), the hospital (increased costs, extra days of stay), patients in other units of the hospital (boarding in upstream units while awaiting beds), care team and physicians (increased workload, chaos), and potential patients not yet in the hospital (ambulance diversion due to ED crowding due to boarding).

The emerging field of healthcare systems engineering (HSE) is uniquely positioned and equipped to balance these various objectives in order to achieve the best outcomes for all parties while maintaining patient quality of care. HSE uses principles of systems engineering (originally developed and honed for manufacturing, warehousing, and distribution) to address the logistical challenges within healthcare such as resource use, scheduling, workload balancing, and facility layout that are typically outside of the clinical scope of healthcare providers.

We note that despite the importance of discharge efficiency and the many associated problems in practice, as illustrated previously, there is an apparent dearth of research on improving IU discharges using principles of HSE. Thus, we attempt to confront this challenge by examining each of the three above-mentioned major decision points associated with an IU discharge from an HSE perspective.

1.4 Research Questions

We address the following questions in this research:

Contribution 1. With regards to disposition determination/discharge initiation:

- Q1. What factors, on admission, predict a general medicine inpatient's eventual discharge disposition to a home or non-home location?
- Q2. How can we develop an easily implementable and intuitive disposition prediction decision aid for healthcare providers such as admitting nurses?

Contribution 2. With regards to day-of-discharge target strategies:

- Q3. What are some effective and feasible IU discharge target strategies, and how can we estimate their potential effects on both IUs and upstream units?
- Q4. What are the realistic benefits of a pilot implementation at a hospital IU, and what are the associated challenges?
- Q5. Is our proposed strategy, and method to evaluate it, generalizable across different IUs and hospitals?

Contribution 3. With regards to an ancillary service provider's patient prioritization in the IU:

- Q6. How can we model the daily process for an ancillary service provider and its relationship with various outcome measures across IU and upstream patients?
- Q7. How can this model be used to identify an optimal patient sequencing strategy for an ancillary service provider to optimize the outcome measures in question? How sensitive is the optimal solution to the problem input characteristics?

1.5 Research Contributions

1.5.1 Contribution 1 (Questions 1 and 2): *An Early-Warning Tool for Predicting-at-Admission the Discharge Disposition of a Hospitalized Patient*

The objective of this study was to identify clinical and health services factors that predict discharge disposition (home vs. non-home) for a general medicine population. Once a satisfactory predictive model has been constructed, our further objective was to derive a decision tool that can be implemented in practice.

We performed a retrospective study using 4760 admissions records of patients discharged from the Boston VA facility's general medicine service in 2013. Utilizing logistic regression with backward selection in a train-test approach, we developed a predictive model for non-home discharges which incorporates both clinical factors present on admission and health history factors that are often considered by clinicians in practice. We used the standardized coefficients from the final model to develop a point-based additive scoring system, which was implemented in a sheet-based decision tool for practical implementation.

Our final logistic regression model identifies a small set of factors, some current and some historical, that can predict with high accuracy whether a patient recently admitted to the general medicine service is likely to be discharged to a non-home location. The additive score derived from this model closely follows the model's predictive performance. We have delivered the sheet-based scoring tool to the Boston VA general medicine service, and plan to support them in its implementation.

This contribution was funded by the New England Veterans Resource Center (NE-VERC) and involved medical collaborators (Dr. Steven Simon, Associate Chief of

Staff, Brockton Campus, and Chief, Geriatrics and Extended Care, and Michael Donlin, nurse practitioner at the West Roxbury site), both affiliated with Boston VA. Findings of this work are *in review with Health Services Management Research*; see Chapter 2 for more details.

1.5.2 Contribution 2 (Questions 3-5): *The n-by-T Target Discharge Strategy for Inpatient Units*

Questions 3 and 4

The objectives of this study were to develop day-of-discharge targets for IUs, evaluate their potential impact upon both IU discharges and upstream patient boarding, and then perform a trial of the most promising target in a real-world setting.

We used retrospective data consisting of 1604 records of patients discharged in 2013 from the trauma unit of Kettering Medical Center (KMC) in Dayton, OH to develop a validated discrete-event simulation model of a typical day-of-discharge on a trauma IU. We used this simulation model to estimate the impact of implementing the novel n-by-T discharge strategy, which gives units a target number of patients, n, to be discharged by a target time of day, T. We evaluated the effect of various combinations of n and T under different occupancy rates.

Our simulation model accurately replicates an average day on the trauma IU. It predicts that n-by-T can offer substantial improvements over the current system in both earlier discharge completion time of day (up to 3.17 hours) and reduced upstream boarding (up to 15.4%). The model further demonstrates that n is a more critical factor than T, and that the potential benefits of n-by-T increase with increasing occupancy rate. A pilot on the unit demonstrated that our model accurately predicted the outcomes of successful 2-by-12 implementation (~2 hr advancement in mean discharge completion time and ~15% reduction in mean upstream boarding time), although it also identified several challenges to such implementation highlighted further in our *recent paper in Medical Decision Making* and elaborated in Chapter 3. This work was part of an NSF grant led by Dr. Parikh and in collaboration with Dr. Nancy Pook (Emergency Physician at KMC).

Question 5

During the summer of 2016, we had an opportunity to extend our research from Contribution 2 to Maine Medical Center (MMC) in Portland, ME, under the guidance of Dr. Peck. The objective of this study was to evaluate the generalizability of the modeling approach and *n*-by-*T* target discharge strategy developed in the study with KMC.

Employing the same modeling approach, we evaluated *n*-by-*T* for a neurology/trauma unit at this new hospital, using retrospective data consisting of 1303 records of patients discharged in 2015. Analysis of the model outcomes indicated the model's robustness towards adapting to a new unit at a new hospital. The model also predicted similar outcomes for an *n*-by-*T* implementation at this new unit: up to 2.56 hours advancement in completion time and 13.57% reduction in upstream boarding time. This study was *recently published in the conference proceedings of the 2017 Industrial and Systems Engineering Research Conference*, for which it received the *best healthcare systems track paper award*. See Chapter 4 for further details.

1.5.3 Contribution 3 (Questions 6 and 7): *Sequencing Daily Patient Workload for an Ancillary Service Provider*

The objective of this study was to develop optimal (or near-optimal) patient workload sequencing strategies that would enable an ancillary service provider (ASP) in an inpatient unit to balance discharge-ready patients and other patients (newly-arriving and recurring), while ensuring patient due dates are met, in order to minimize upstream boarding time.

To address this stochastic sequencing problem, we developed a scenario-specific MIP model of a typical day for an ASP in an inpatient unit. We combined this model with a scenario sampling optimization approach and a simulated annealing meta-heuristic to derive robust and easily implementable strategies for the ASP. An experimental evaluation of our combined approach using the retrospective dataset from MMC and interviews with ASPs at this hospital revealed strategies, specific to the different system configurations considered in our design, that were robust to variability within these systems, averaging 13% deviation from scenario-specific optimality. We further compared these derived strategies to several simple, practical strategies and found that such strategies either trade simplicity for worse performance or bring better performance at the expense of constraint violations.

This contribution was part of an NSF grant led by Dr. Parikh and Dr. Kong, in collaboration with Dr. Peck who sponsored the work at MMC. Findings of this study will be submitted to *IEEE Transactions on Automation Science and Engineering (special issue on Smart and Interconnected Healthcare Delivery Systems) by October 1, 2017*; see Chapter 5 for further details.

2 AN EARLY-WARNING TOOL FOR PREDICTING-AT-ADMISSION THE DISCHARGE DISPOSITION OF A HOSPITALIZED PATIENT*

2.1 Background

The US Accountable Care Act (ACA) highlights value-based reimbursement, which encourages hospitals to focus on high-quality care at lower cost. While the Department of Veterans Affairs (VA) health system is not necessarily reimbursement based, it strives to manage quality and resource utilization via evidence-based practice and continuous measurement and improvement. Managing patient flow effectively through VA medical centers requires the proactive identification of appropriate level of care and services; this strategy has also been identified in the ACA. This activity is a vital first step towards effective patient care management, prompt discharge planning, and reduction in service delays.

Early planning and coordination from the healthcare team, including physicians, social workers, rehabilitation specialists, and post-acute care services, improves care quality and access, while managing costs (Schlegel et al., 2004; De Guise et al., 2006). The ability to predict discharge disposition – whether a patient can return home or requires placement in a care facility – could expedite rehabilitation, improve coordination of care among consultants, prepare caregivers, and help community agencies plan for needed resources. It also helps reduce length of hospital stay, which, in turn, may

* Ballester, N., Parikh, P. J, Donlin, M. & Simon, S. (2017). An early-warning tool for predicting-at-admission the discharge disposition of a hospitalized patient. *Health Services Management Research* (in review).

mitigate the risks of hospitalization and improve patient recovery (Hagino et al., 2011; Ekstrand et al., 2008; Simonet et al., 2008; Tanaka et al., 2008; Meijer et al., 2004).

The primary objective of this study was to identify both clinical and health utilization factors (at index and previous hospitalizations) that predict discharge disposition for Veterans within 24 hours of admission to the general medical service at a VA medical center.

2.2 Methods

2.2.1 Setting

To develop our approach, we collaborated with the medical staff at the West Roxbury campus of the VA Boston Healthcare System (VA-BHS), a medium-sized, tertiary-care VA hospital affiliated with Harvard Medical School and Boston University School of Medicine. All patients were cared for by internal medicine resident teams on typical mixed medical/surgical floors throughout the 168-bed hospital. Annually, the general medical service admits and discharges approximately 6,000 Veterans.

At the time of the study, discharge planning occurred within an interdisciplinary group consisting of a nurse case manager, social worker, and a clinician representing the medical team (attending physician, resident physician, and nurse practitioner or physician assistant). Consultations to other services such as physical therapy and occupational therapy were made based on the individual assessments of these groups, mostly prompted by clinical judgment. No formal tool was used to guide assessment of patients' needs for placement in a facility after discharge.

2.2.2 Data Collection

We obtained data from the Corporate Data Warehouse of the VA-BHS for January 1 through December 31, 2013. We identified 4,817 discharge records (of which 3,187 were unique patients) admitted to and discharged alive from the general medical service. After excluding 57 records (1.18%) with missing discharge disposition, the final dataset consisted of 4,760 records. We considered factors for inclusion in this study which would be readily available to the care team within 24 hours of admission.

Index Admission: For the index admission, we ascertained demographic information (i.e., age, sex, race, presence of non-VA health insurance, and marital status), clinical factors (primary diagnosis, number of diagnoses), source of admission, and specialty of the admitting ward. The primary diagnosis at the time of admission is not an available field in VA administrative data; however, the primary hospitalization diagnosis, recorded clinically at the time of discharge, is routinely transcribed from the admission history and physical note, and thus represents the likely primary diagnosis at the time of admission. These diagnoses were grouped into 19 categories based on ICD-9 standard code groups. Admission sources included VA nursing home, VA domiciliary, transfer from other VA hospital, outpatient treatment, and other direct (e.g., walk-ins, directly admitted from home, transfers from non-VA facilities). Admitting ward specialties included general (acute medicine), cardiac intensive care unit (ICU), medical ICU, medical step down, telemetry, and hospice for acute care. We included ICU patients because the variables considered in predicting their disposition are comparable to those patients admitted to non-critical care units. We further derived the 31 Elixhauser comorbidities using the updated ICD-9-CM coding schema of Quan et al. (2005). This study was approved by the VA Boston Institutional Review Board.

Historical Factors: We also derived several historical clinical and health services factors using a 12-month "look back" into 2012 records of each of the unique patients. The clinical factors included the primary diagnosis of the immediately preceding hospital admission, the number of diagnoses on the immediately preceding admission, and the discharge disposition for the immediately preceding admission. The health services/utilization factors included number of previous admissions in the past 12 months prior to the index admission, and an indicator of whether the index admission was an all-cause readmission within 30 days.

Main Outcome Measure: The main outcome was the patient's discharge disposition, home vs. non-home. Patients discharged to the community, including those who were homeless and referred to a shelter, were considered discharged to "home." Non-home locations included VA nursing homes, known internally as Community Living Centers (CLC), and non-VA nursing homes.

2.2.3 Data Analysis

Due to pragmatic limitations to conducting a prospective validation, we adopted the standard derivation-validation approach. Accordingly, we split the records randomly into two subsets, 70%-30%. Using the 70% data (the derivation set, N=3351), we built a case-mix adjusted logistic regression model of non-home discharge disposition (using backward selection), with sex forced into the model.

After the first model was built, admission from a VA nursing home care unit (NHCU) was found to have a disproportionately large odds ratio (~145), attributable to the fact that nearly all patients admitted from a NHCU (40/42, or 95%) were discharged to a non-home location. Consequently, admission from NHCU was deemed as the major, and sufficient, factor for the hospital care team; i.e., if a patient is admitted from NHCU, they will almost certainly return to NHCU or to another non-home location. In order to build a predictive model for patients who do not meet this first criterion, these records were removed from both the derivation and validation datasets for subsequent analyses. Consequently, the final multivariate model does not include NHCU admission as a predictor.

Once the final multivariate model was derived, we used the remaining 30% data (the validation dataset, N=1409) to estimate the model's predictive power based on area under the operating curve (AUC) values. A score for clinical application was derived from the final model. Using the standardized logistic regression coefficients, each factor in the final model was assigned a relative weight out of a 20-point scale; the score for a patient would then be the sum of these weights (if the corresponding factors were present for that patient). The 20-point scale was chosen as the best balance between discrimination (to allow enough separation between factors) and ease-of-use. These weights were rounded to integer values for ease of addition in practice. In deciding whether to round each weight up or down, our objective was to maximize the correlation between the total score for a patient and the predicted probability of non-home discharge for that patient from the logistic regression model (across all records in the derivation data set). Continuous predictors (age and number of diagnoses) were separated into categories based on the distribution of the data; the weight assigned to each of these was then divided among the corresponding categories (these divisions were considered as additional decision variables in the optimization). The sum of all the weights in the score was constrained to be 20 (i.e., if a patient exhibited all predictors from the final model, they would be assigned a score of 20).

Since the coefficients in the logistic regression model (and the corresponding factor score weights) could be either positive (predictive of non-home discharge) or negative (protective factors), we separated them into two positive additive subtotals in the scoring tool, one for the predictive factors and one for the protective factors. The latter is then subtracted from the former to get the final score for a patient. Clinical practitioners were consulted in order to ensure that the questions relating to each factor from the model were phrased in a way that would make sense to a care provider. We then determined a threshold value beyond which the patient was likely to go non-home, considering an acceptable sensitivity and specificity of the score, and various clinical considerations suggested by our medical collaborators. SAS v9.4 was used for all statistical analyses.

2.3 Results

Of the 4760 patients, 485 (10.2%) were discharged to a non-home location, which included VA nursing home (n=301), VA medical centers (n=129), community nursing home (n=53), VA domiciliary (n=1), and other government hospital (n=1).

Table 2-1 indicates that demographic variables such as age, married status, and white race were independent predictors of the patient’s disposition location. Several other factors around admitting source, admitting ward, clinical diagnosis, and comorbidities were also significant.

Table 2-1: Characteristics of the Patients at Admission

Characteristic	Home n = 4275 90%	Non-Home n = 485 10%
Age, years (mean ± SD)***	70.29 ± 13.43	73.64 ± 12.72
Female, N (%)	171 (4%)	20 (4%)
Married, N (%)*	1597 (37%)	135 (28%)
Race, N (%)		
White, not of Hispanic Origin**	1764 (41%)	244 (50%)
Black, not of Hispanic Origin	157 (4%)	12 (2%)
Hispanic, White	21 (<1%)	1 (<1%)
Asian or Pacific Islander	7 (<1%)	0 (<1%)
Hispanic, Black	4 (<1%)	0 (<1%)
American Indian or Alaska Native	2 (<1%)	1 (<1%)
Insurance coverage,	3333 (78%)	364 (75%)
Primary diagnosis, N (%)		
Infectious and parasitic diseases	131 (3%)	23 (5%)
Neoplasms***	176 (4%)	47 (10%)
Endocrine, nutritional, and metabolic diseases, and immunity disorders	225 (5%)	15 (3%)
Diseases of the blood and blood-forming organs	84 (2%)	7 (1%)
Mental disorders	392 (9%)	29 (6%)
Diseases of the nervous system**	55 (1%)	13 (3%)
Diseases of the sense organs	19 (<1%)	2 (<1%)
Diseases of the circulatory system**	1037 (24%)	80 (16%)
Diseases of the respiratory system*	564 (13%)	80 (16%)
Diseases of the digestive system	378 (9%)	31 (6%)
Diseases of the genitourinary system	299 (7%)	26 (5%)
Diseases of the skin and subcutaneous tissue	160 (4%)	14 (3%)
Diseases of the musculoskeletal system and connective tissue**	136 (3%)	29 (6%)
Congenital anomalies	7 (<1%)	0 (0%)
Symptoms, signs, and ill-defined conditions	401 (9%)	43 (9%)
Injury and poisoning***	194 (5%)	43 (9%)
External causes of injury and supplemental classification	17 (<1%)	3 (1%)
Number of diagnoses (mean ± SD)***	10.19 ± 3.75	11.65 ± 3.28
Source of admission, N (%)		
From home or other non-VA community location**	3392 (79%)	347 (72%)
From VA outpatient clinic	856 (20%)	90 (19%)
Transfer from another VA hospital**	22 (1%)	7 (1%)
VA nursing home care unit***	2 (<1%)	40 (8%)
Transfer from non-VA hospital	2 (<1%)	0
VA domiciliary	1 (<1%)	1 (<1%)
Nursing Unit on Admission, N (%)		
General medicine, without telemetry implemented***	2297 (54%)	319 (66%)
General medicine, with telemetry implemented***	1494 (35%)	118 (24%)
Cardiac intensive care unit	242 (6%)	18 (4%)
Medical step-down§	128 (3%)	14 (3%)
Medical ICU	113 (3%)	18 (4%)
Hospice for acute care	1 (<1%)	0
Elixhauser comorbidities, N (%)		

Congestive heart failure	867 (20%)	109 (22%)
Cardiac arrhythmia*	1321 (31%)	170 (35%)
Valvular disease	316 (7%)	31 (6%)
Pulmonary circulation disorders	170 (4%)	19 (4%)
Peripheral vascular disorders	367 (9%)	42 (9%)
Hypertension uncomplicated*	1910 (45%)	186 (38%)
Hypertension complicated*	614 (14%)	49 (10%)
Paralysis**	55 (1%)	16 (3%)
Other neurological disorders***	288 (7%)	58 (12%)
Chronic pulmonary disease	1254 (29%)	146 (30%)
Diabetes uncomplicated	1198 (28%)	132 (27%)
Diabetes complicated	304 (7%)	38 (8%)
Hypothyroidism	217 (5%)	32 (7%)
Renal failure	859 (20%)	91 (19%)
Liver disease	505 (12%)	59 (12%)
Peptic ulcer disease, excluding bleeding	28 (1%)	2 (<1%)
AIDS/HIV	16 (<1%)	4 (1%)
Lymphoma	68 (2%)	8 (2%)
Metastatic cancer***	124 (3%)	37 (8%)
Solid tumor without metastasis***	353 (8%)	71 (15%)
Rheumatoid arthritis/collagen vascular disease	58 (1%)	11 (2%)
Coagulopathy	162 (4%)	11 (2%)
Obesity	238 (6%)	30 (6%)
Weight loss	82 (2%)	18 (4%)
Fluid and electrolyte disorders	587 (14%)	81 (17%)
Blood loss anemia	18 (<1%)	2 (<1%)
Deficiency anemia*	208 (5%)	35 (7%)
Alcohol abuse**	809 (19%)	69 (14%)
Drug abuse	261 (6%)	26 (5%)
Psychoses***	192 (4%)	52 (11%)
Depression	848 (20%)	105 (22%)

§The Medical Step-Down Unit is principally intended for patients requiring more frequent nursing contact and/or more intensive respiratory monitoring than the general medical units but not requiring one-to-one nursing care or other intensive care of the critical care units.

*, **, and *** indicate factors found significant at α=0.05, α=0.01, and α=0.001, respectively, in bivariate analysis using the Derivation set.

Some of the categories may not add up to 100% due to missing values not reported here.

Table 2-2 highlights that a previous admission diagnosis of diseases of the nervous system, diseases of the circulatory system, or external causes of injury and supplemental classification, as well as total number of diagnoses, were independent historical clinical predictors, while number of previous admissions in the past 6 months and previous discharge to a community hospital, VA medical center, or VA NHCU were independent health services predictors of the discharge disposition for the index admission.

Table 2-2: Historical Clinical and Health Services Variables for the Cohort

Characteristic	**Home** n = 4275 90%	**Non-Home** n = 485 10%
Previous primary diagnosis, N (%)		
Infectious and parasitic diseases	64 (1%)	7 (1%)
Neoplasms	131 (3%)	25 (5%)
Endocrine, nutritional and metabolic diseases, and immunity disorders	132 (3%)	11 (2%)
Diseases of the blood and blood-forming organs	54 (1%)	7 (1%)
Mental disorders	485 (11%)	64 (13%)
Diseases of the nervous system*	44 (1%)	11 (2%)
Diseases of the sense organs	19 (<1%)	2 (<1%)
Diseases of the circulatory system***	664 (16%)	47 (10%)
Diseases of the respiratory system	309 (7%)	24 (5%)
Diseases of the digestive system	228 (5%)	22 (5%)
Diseases of the genitourinary system	167 (4%)	9 (2%)
Diseases of the skin and subcutaneous tissue	87 (2%)	10 (2%)
Diseases of the musculoskeletal system and connective tissue	91 (2%)	12 (2%)
Congenital anomalies	2 (<1%)	0
Symptoms, signs, and ill-defined conditions	268 (6%)	35 (7%)
Injury and poisoning	102 (2%)	16 (3%)
External causes of injury and supplemental classification***	160 (4%)	83 (17%)
Previous discharge disposition, N (%)		
Return to community-independent	2730 (64%)	294 (61%)
VA medical center***	135 (3%)	43 (9%)
Community nursing home	38 (1%)	8 (2%)
VA nursing home care unit***	24 (1%)	11 (2%)
Community hospital*	6 (<1%)	6 (1%)
VA domiciliary	1 (<1%)	0
Other government hospital	0	1 (<1%)
Other placement/unknown (not specified)	0	1 (<1%)
Previous number of diagnoses (mean ± SD)***	9.93 ± 4.3	11.1 ± 3.4
Current admission is an all-cause readmission within 30 days, N (%)*	1255 (29%)	175 (36%)
Number of admissions in past 6 months (mean ± SD)*	1.42 ± 2.1	1.59 ± 1.84
Number of admissions in past 12 months (mean ± SD)	2.27 ± 3.39	2.33 ± 2.45

*, **, and *** indicate factors found significant at α=0.05, α=0.01, and α=0.001, respectively, in bivariate analysis using the Derivation set.
Some of the categories may not add up to 100% due to missing values not reported here.

Table 2-3 shows the case-mix adjusted logistic regression model, along with the odds ratios (OR) and 95% confidence interval (CI) based on the derivation dataset; OR greater than 1 indicate higher chance of placement in a facility (non-home), while OR less than 1 indicate higher chance of going home. The AUC of this model was 0.75 for the derivation dataset; using the validation set, the AUC was 0.74.

Table 2-3: Case-mix Adjusted Model for Disposition Prediction of Patients Not Admitted from Nursing Home Care Units, Using the Derivation Dataset

Predictor	**Odds Ratio (95% CI)**	***p*-Value**
Age	1.020 (1.009-1.030)	0.0001
Female Sex	0.838 (0.426-1.649)	0.6094
Primary diagnosis		
Neoplasms	2.714 (1.733-4.250)	<0.001
Diseases of the nervous system	2.525 (1.255-5.080)	0.0094
Diseases of the musculoskeletal system and connective tissue	2.549 (1.523-4.269)	0.0004
Number of diagnoses[§]	1.151 (1.108-1.196)	<0.001
Previous primary diagnosis		
Diseases of the circulatory system	0.541 (0.353-0.828)	0.0047
External causes of injury and supplemental classification	2.578 (1.732-3.837)	<0.001
Previous discharge disposition		
Community hospital	10.328 (2.066-51.631)	0.0045
VA medical center	4.214 (2.599-6.834)	<0.001
VA nursing home care unit	3.593 (1.489-8.669)	0.0044
Comorbidities		
Hypertension uncomplicated	0.615 (0.473-0.800)	0.0003
Hypertension complicated	0.309 (0.200-0.476)	<0.001
Other neurological disorders	1.699 (1.157-2.497)	0.0069

[§] Because discharge diagnosis by definition is not available on admission, the scoring system uses as a proxy to active diagnoses being addressed on admission.

Among diagnoses on admission of the index hospitalization, neoplasms (OR = 2.71, CI = 1.73–4.250), diseases of the nervous system (OR = 2.53, CI = 1.26 – 5.08), and diseases of the musculoskeletal system and connective tissue (OR = 2.55, CI = 1.52 – 4.27) were associated with discharge to a non-home location. In contrast, historical primary diagnosis of circulatory system disease was associated with lower likelihood of discharge to a non-home location (OR = 0.54, CI = 0.35 -0.83), as were the presence of both uncomplicated hypertension (OR = 0.62, CI = 0.47 – 0.80) and complicated hypertension (OR = 0.31, CI = 0.20 – 0.48) during prior hospitalization. The previous primary diagnosis of external causes of injury and supplemental classification indicates a higher likelihood of patient discharge to a non-home location (OR = 2.58, CI = 1.73 – 3.84), as does the comorbidity of other neurological disorders (OR = 1.70, CI = 1.16 – 2.50).

The 3 previous discharge disposition locations of community hospital, VA medical center, and VA NHCU are associated with high odds ratios (OR = 10.33, 4.21, 3.59, respectively), indicating that if the patient had been discharged to one of these locations after the prior admission, then this patient is very likely to go to a non-home location again upon discharge from the index hospitalization.

The score developed for clinical application is shown in the Appendix at the end of this chapter (Section 2.5). The weights assigned to the factors in the score achieved an 84% correlation with the logistic regression model probabilities for the derivation set. At a classification threshold of 5 points, the score achieved a sensitivity (number of non-home discharges correctly identified as such) and specificity (number of home discharges correctly identified as such) of 83% and 46%, respectively (Figure 2-1). When tested on the validation set, the score with this threshold achieved 82% sensitivity and 48% specificity, suggesting that the score is robust in predicting non-home discharges.

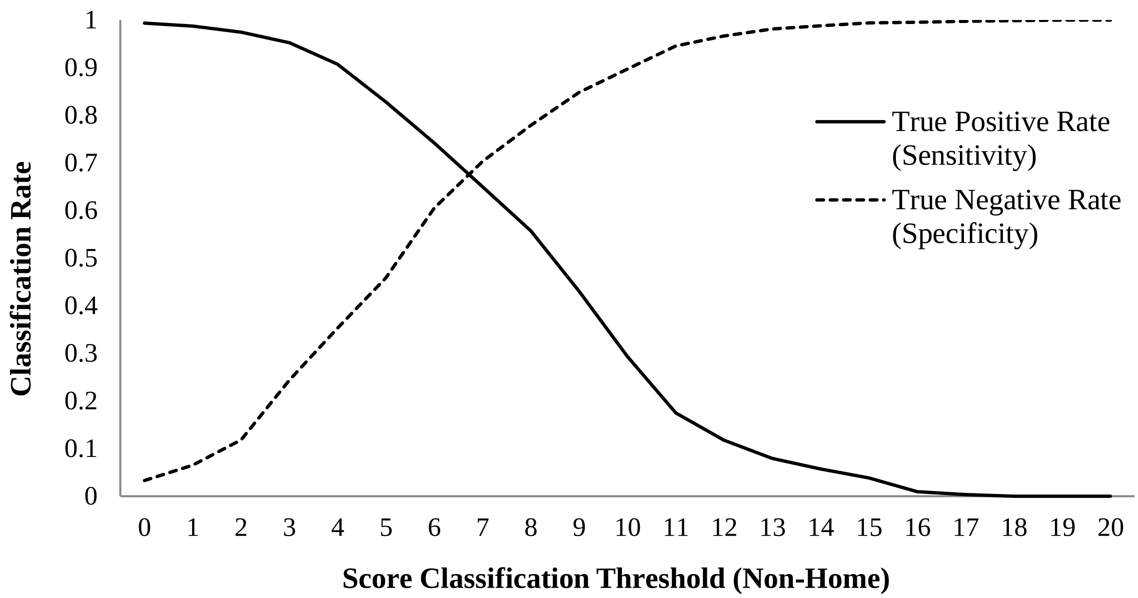


Figure 2-1: Effect of Classification Threshold on Score Sensitivity and Specificity

2.4 Discussion

In this retrospective study of an entire year's acute care hospitalizations at a tertiary care VA medical center, we identified variables that predict, at the time of admission, a patient's likely discharge to a non-home location. We found that nearly all patients admitted from a VA nursing home care unit were discharged to a non-home location, likely the nursing home care unit from which they were admitted. Using a derivation-validation approach, we determined that older patients, those admitted with neurologic, oncologic, and musculoskeletal primary diagnoses, those with larger numbers of diagnoses, and those previously hospitalized and discharged to a VA medical center were more likely to be discharged to a non-home location during the index hospitalization. In contrast, those with hypertension and a prior hospitalization with a primary diagnosis of a circulatory disorder were less likely to be discharged to a non-home location in the index hospitalization. These findings, validated in a subsequent logistic regression model, led to the creation of a clinically-relevant score that can be used to predict at the time of admission, with good sensitivity and acceptable specificity, discharge to a non-home location.

Early, accurate, and effective discharge planning has emerged as a high priority for both patients and hospital systems (Cherlin et al., 2013). An important aspect of discharge planning is predicting, as soon as possible and ideally at the time of admission, the post-acute care disposition location that the patient will need on discharge. Knowing with a high degree of certainty whether the patient will be able to be discharged home versus another location can facilitate planning, guide decision-making during the acute hospitalization, and foster improved communication between and among patients, family and care team members. The result is a potential increase in the system efficiency and reduction in the patient's length of stay in the acute care facility. There is a clear distinction between predicting discharge location and determining optimal discharge for patient care quality, satisfaction, safety, and lowest cost; our study seeks to achieve the former only, in order to facilitate discharge planning from day one.

Our study is one of the first to predict discharge disposition among patients admitted to general medical units with a wide array of medical conditions in a VA medical center. It is also one of only a few to deliver an implementable predictive tool based on the statistical analysis conducted in the study. While current clinical factors such as diagnosis and comorbidities typically form the basis of a care provider's instinctive prediction of the eventual disposition location, we uncovered a few historical clinical and health utilization factors that also seem to play an important role in this decision-making process in practice. The validated tool that was derived based on these findings can help guide planning and decision making on a daily basis.

Several studies have focused on predicting discharge disposition among specific patient populations such as stroke, traumatic brain injury, total joint arthroplasty, geriatric, trauma, or cardiac surgery (De Guise et al., 2006; Brauer et al., 2008; Pohl et al., 2013; Cuthbert et al., 2011; Sharareh et al., 2014; Gabbe et al., 2005); some have proposed various prediction tools (Barsoum et al., 2010; Wachtel et al., 1987; Beaulieu et al., 2014; Pattakos et al., 2012). Simonet et al. (2008) developed a validated score predicting risk of discharge to a post-acute care facility for general medicine patients, both on admission (Day 1) and day 3 of hospital stay. While their study had fewer than 400 patients, most likely due to its prospective nature, 3 out of 5 of significant factors in their Day 1 model were similar to our findings: age, number of diagnoses, and admission source. Unlike the present study, they did not find historical health utilization factors (i.e., hospital and ED visits in the past 3 months) to be independent predictors. In further contrast, they used an aggregate comorbidity index (Charlson's index), not found to predict discharge disposition, while we used the more granular set of 31 Elixhauser's comorbidities, 3 of which were part of the final adjusted model.

In terms of the diagnoses found in this study to be significant with non-home discharge, many were consistent with what clinicians would expect among very ill patients who would likely need post-acute care in a nursing, rehabilitation or specialized facility, such as metastatic cancer, paralysis, and psychoses. Conversely, the factors that seemed to be protective, i.e., predictive of a discharge to home, for example having a diagnosis of hypertension, either complicated or uncomplicated, may simply be an indicator of the absence of more serious or complicated diagnoses.

Lowering the threshold, or cut-point, in the prediction model allows for increased sensitivity at the expense of decreased specificity. The implications of these trade-offs are worth considering further. For instance, while an increase in sensitivity would predict accurately at admission a larger proportion of non-home patients, a number of these would also be false positives (predicting a non-home location when actually the patient goes home). This may be due to the evolving clinical and functional status information along with other factors (e.g., patient/family choice, patient's social network, availability of beds at post-acute care settings, etc.) during the patient's stay. On all those false positive cases, the care provider team would have begun planning for a non-home discharge on Day 1 and continue their effort until such time as it becomes apparent that the patient may in fact be able to realize a discharge to home. This process induces over-utilization of scarce resources, including expert discharge planning and physical therapy consultations. In general, however, our sense is that most clinicians and case managers would favor being surprised by a patient going home rather than being surprised by a patient requiring discharge to a rehabilitation or skilled nursing facility, as planning for the latter normally requires a longer lead time.

In practice, our tool could be used by the patient's care team at admission to classify the patient as a potential non-home discharge. This information would provide an early indicator to the patient and the care team at the beginning phase of the patient's stay when clinical information is sparse, and before other clinical bedside data and functional status assessments have been collected. Having this "early warning" would facilitate discharge planning, as the discharge coordinator could initiate discussion with the patient soon after admission regarding the potential for placement in a facility and begin evaluating alternatives. It is worth noting that the purpose of such an early-warning system is to help the care team to anticipate the potential workload of discharge planning, to promote and enhance communication between providers and the patient, and to expedite overall care coordination associated with non-home discharges, and not to identify an optimal discharge within those 24 hours upon admission.

Our study findings must be viewed in the context of several limitations. First, although we accessed rich clinical data from the corporate data warehouse, this data source does not include a number of measures that may be important in determining discharge disposition, such as the patients' activities of daily living, income level, or level of social support. We used the number of diagnoses as a proxy for the acuity of the patient's condition. Likewise, the marital status of the patient may serve as a proxy for social support. Second, in determining the primary diagnosis and number of diagnoses for a patient admission, the recorded discharge diagnoses associated with that admission were used. At this facility, the primary diagnosis at admission is routinely transcribed as the discharge diagnosis; however, this approach may have resulted in our using some diagnoses that were not actually known at the time of admission. Because discharge diagnosis by definition is not available on admission, the model and scoring system use as a proxy the active diagnosis identified on admission. Third, although we could not identify the eventual disposition (home or non-home) of 129 patients transferred to another VA medical center, we classified them as "non-home," as the eventual disposition was not germane to the disposition outcome of the index hospitalization.

Finally, to develop and validate our early-warning approach, we focused on a specific Veteran patient cohort (general medicine) at one VA facility; while the findings may be generalizable to many similarly sized tertiary care VA medical centers, the tool may have broader applicability in a wide range of hospital settings.

Our study is both confirmatory and exploratory. We confirm previous research conducted on non-Veteran populations and other medical conditions that it is possible to develop a model to predict discharge disposition at admission using readily available factors. We explored the significance of several historical clinical and health services factors, many of which were independent predictors, two of which were part of the final adjusted model. We then developed a validated predictive score; future study should consider implementing this score in actual clinical practice.

2.5 Appendix: A Score for Non-Home Discharge Determination within 24 Hours of Admission to General Medicine

Was patient admitted from a VA Nursing Home Care Unit (NHCU)?
If YES, patient should be treated as a **non-home discharge**
If NO, use score below:

Factors predicting non-home discharge	**Points**	
How old is the patient?		________
56 or younger	1	
57 to 70	2	
71 to 84	3	
85 or older	4	
Does the patient's current primary diagnosis fall into one of the following categories?		________
Diseases of the nervous system	2	
Neoplasms	3	
Diseases of the musculoskeletal system and connective tissue	3	
How many active diagnoses are being addressed on admission?		________
5 or fewer	1	
6 to 10	3	
11 to 14	6	
15 or more	8	
If the patient was discharged from the hospital within the last 12 months was the primary diagnosis "external causes of injury and supplemental classification" (E and V ICD-9 codes)?	4	________
If the patient was discharged from the hospital within the last 12 months, were they discharged to one of the following?		________
Community hospital	1	
VA nursing home care unit	1	
VA medical center	5	
Does the patient currently exhibit the comorbidity of "other neurological disorders" (ELX 9)?	2	________
Subtotal A (*sum up the points for the predictive factors*)		________
Factors predicting discharge to home (protective factors)		
Is the patient female?	1	________
When the patient was last admitted, did the primary diagnosis fall under the category of "diseases of the circulatory system"?	3	________
Does the patient currently exhibit one of the following comorbidities?		
Hypertension, Uncomplicated (ELX 6)	3	________
Hypertension, Complicated (ELX 7)	6	________
Subtotal B (*sum up the points for the protective factors*)		________

	−		=	
Subtotal A	**−**	**Subtotal B**	=	**Final Score**

If Final Score is 5 or greater,
the patient is more likely to be discharged to a non-home location.

3 THE *n*-BY-*T* TARGET DISCHARGE STRATEGY FOR INPATIENT UNITS*

3.1 Background

Healthcare in the US is a complex, multi-step, multi-setting process. In 2013 the national health expenditures amounted to $2.9 trillion, or 17.5% of the US GDP, and of this 32.1% was attributable to hospital care (CDC, 2015a). Despite these expenses, quality of care seems to be on a downward trend; from 2003 to 2009, the mean waiting time of patients in the emergency department (ED) increased 25%, from 46.5 minutes to 58.1 minutes (Hing & Bhuiya, 2012).

This is not merely an isolated symptom of EDs; they are highly connected to inpatient hospitals, with over half of inpatient admissions in the US in 2009 originating in the ED (Weiss et al., 2014). Because crowding and boarding in the ED and other units upstream from inpatient units, such as Post-Anesthesia Care Unit and Surgical Intensive Care Unit , have been shown to negatively affect quality of care, patient safety, and patient satisfaction, reductions in these barriers would likely reap benefits to both patients and providers (Crawford et al., 2014; Bernstein et al., 2009; Liu et al., 2009; McCarthy et al., 2009; Pines et al., 2009).

Studies have suggested that improving inpatient bed availability by balancing inpatient discharges with admissions can alleviate, if not eliminate entirely, upstream boarding and crowding (Powell et al., 2012; Wong et al, 2010; ACEP, 2009; M.

* Parikh, P. J., Ballester, N., Bertsch, K., Kong, N., & Pook, N. (2017). The *n*-by-*T* target discharge strategy for inpatient units. *Medical Decision Making*, *37*(5), 534-543.

Vermeulen et al., 2009; Kravet et al., 2007; Yancer et al., 2006; Forster et al., 2003). According to one study, 1 in 4 inpatients could have been discharged earlier than they were (Srivastava et al., 2009). With over 35.1 million inpatient discharges in the U.S. in 2010 (CDC, 2015b), it is critical to understand key factors such as patient condition and necessary care, anticipated length of stay, patient needs upon discharge, and where the patient will go upon discharge during inpatient discharge planning (Shepperd et al., 2013). When a smooth coordination of the inpatient discharge process fails to take place, it delays inpatient bed release, which delays the transfer to inpatient beds for newly admitted patients from various upstream units.

Recently, timing the inpatient discharges to reduce ED boarding of admitted patients by shifting the discharge distribution curve has been suggested (Powell et al., 2012). Although such an approach seems attractive, very little has been suggested in the literature as to how this can be achieved. Anecdotally, some hospitals have employed their own strategies to improve inpatient discharge processing, such as incentivizing physicians to finish their discharge orders earlier in the morning, and even adding overtime or temporary staff during the latter part of the day to help execute planned discharges. But there is lack of clear evidence suggesting the benefits of such strategies.

We contend that the complexity of the inpatient discharge process within a unit, and variances across units in a single hospital, render it difficult to devise a generic, optimal, strategy. In lieu of this, it is possible to develop targets that the care providers in the inpatient unit could aim for each day to realize substantial improvements. To this extent, we propose a novel n-by-T target strategy, which suggests discharging n patients (deemed ready for discharge on a given day) by the Tth hour of the day. For instance, 1-

by-10 means that one inpatient should be discharged by 10 a.m., while 2-by-12 means that two patients should be discharged by 12 noon. This strategy suggests that if the order writing times by the physician are advanced and discharge process length is reduced, then the inpatient unit could achieve the target of discharging a predetermined number of n patients by the Tth hour. The goal is to achieve an improved synchronization of the availability of inpatient beds with the demand of inpatient beds from upstream units to smooth patient flow throughout the hospital. Our motivation to devise such a strategy came from preliminary studies which suggested that reducing discharge process time by unit-allowed maximum of 25% and advancing order writing times by a maximum of 3 hours, independently, resulted in benefits of 8% and 9.1%, respectively, only if implemented unit-wide, across all to-be-discharged patients. Given the difficulty of implementing such strategies at the unit under other process and staffing constraints, the hospital staff preferred the proposed *n*-by-*T* strategy, that required reducing both discharge process times and advancing order writing times (a hybrid strategy) for only a fraction of discharge-ready patients, while not imposing excessive work on the nursing staff during the morning.

Our focus in this study is addressing the following research questions: *to what extent does the n-by-T target strategy advance the discharge completion times and reduce upstream boarding? How sensitive are these benefits to the inpatient unit's occupancy rate? What benefits and challenges might be experienced during a pilot implementation?*

3.2 Methods

Our study was conducted in two phases. Phase I dealt with understanding and representing the current discharge process in the unit via a simulation model in order to evaluate various n-by-T strategies over varying occupancy rates. Phase II dealt with conducting a pilot implementation (based on our findings in Phase I) in a live inpatient unit.

3.2.1 Setting

We focused on an inpatient trauma unit at Kettering Medical Center (KMC), the flagship hospital in the Kettering Health Network – a faith-based hospital network in the Midwest U.S. KMC was founded in 1964 and currently houses 386 inpatient beds. The hospital has nearly 50,000 emergency visits and over 20,000 inpatient admissions annually. The facility has previously been recognized by the U.S. News and World Report as one of the best regional hospitals and by Truven Health Analytics as a top 100 hospital nationwide. Our research focused on one unit of the hospital: a 21-bed inpatient trauma unit, which completed 1,789 inpatient discharges during 2013. This study was approved by KMC's Institutional Review Board.

3.2.2 Data Collection

We used two modes of data collection at the unit: job shadowing to map the current process, and retrospective, de-identified, patient data from the hospital's electronic health record (i.e., Epic) to understand system inputs and outcomes. A collective of over thirty hours were spent in job shadowing the unit nurses to map the steps followed by them when discharging a patient, starting from the physician writing the discharge order all the way to the nurses physically transferring the patient out of the inpatient room. The retrospective data from Epic included time-stamps for order writing and discharge completion for each of the 1,789 discharged inpatients. We were also provided time-stamps for bed requests from upstream units for each day in 2013. Descriptive statistics were used to identify the distributions for the model inputs.

3.2.3 Outcomes of Interest

We focused on four measures, two time-based and two capacity-based. The two time-based measures were 1) mean discharge completion time, measured as the mean time of day when patients are physically discharged from the inpatient room, and 2) mean boarding time of upstream patients, measured as the difference of when the bed request was placed and when the patient actually occupied the inpatient room (including variable transportation times). For this inpatient unit, the upstream units included the ED, Surgery, Medical/Surgical Intensive Care Unit (MSICU), Surgical Intensive Care Unit (SICU), Clinical Decision Unit (CDU), Coronary Care Unit (CCU), Cardiac, Dialysis, and Other (in order of frequency). The two capacity-based measures were related to an increase in the annual availability of 1) inpatient bed hours (due to possible advancement in the mean completion time) and 2) upstream bed hours (due to possible reduction in mean boarding times).

3.2.4 Phase 1: Modeling Current and *n*-by-*T* Discharge Strategies

At a micro level, each unit handles their discharges slightly differently given the patient cohort and acuity, physician rounding patterns, staffing levels (e.g., nurse, social worker, case manager), disposition locations, and bed capacity. The unit staff ensures that all the vital elements of the discharge plan are completed to achieve a timely discharge: e.g., discharge orders, patient education, medication reconciliation, instructions to patient, physical/occupational therapy, insurance approvals, availability at disposition location, and transportation. The room then must be cleaned by the hospital cleaning staff, only after which it becomes available in the electronic health system (i.e., EPIC) to allow the transfer of a patient (at an upstream unit with an outstanding bed request) into this room at this unit.

Based on our observational study and preliminary analysis of the data, we realized that, *at a macro level*, the overall discharge process can be aggregated into 4 temporal events; 1) time of day when discharge order is written by the physician, 2) length of time to accomplish all discharge processes (starting from a written order until patient is physically transferred out of the room), 3) time of day when the bed request is placed for a patient in the upstream unit, and 4) time of day this patient enters the empty room. The length of time to clean the bed after a discharge and the length of time to transport a new patient into the room are two secondary, but also important, elements. This allowed us to develop an aggregate process map depicting the patient flow that was used in developing a discrete-event simulation model (see Figure 3-1). An aggregate approach was also deemed most appropriate by the hospital staff in order to identify and evaluate a generic strategy with the potential of implementation across other inpatient units at this hospital.

The simulation model was designed to emulate a typical 24-hr day-of-discharge process (midnight to midnight) with multiple discharges based on the unit-specific data. Each patient who was to be discharged on a given day was assigned a specific time of day by when their discharge order would be written by the physician and the subsequent amount of time that is required to accomplish the discharge process before discharging the patient. Once the discharge process was complete, and after the time to clean the room had elapsed, the inpatient bed was made available for boarding patients in the upstream units. These patients continued to arrive, starting midnight, and demand inpatient beds based on a non-stationary Poisson arrival rate per hour of day. They were held in a queue (to emulate boarding) until an inpatient bed was available, at which point, after some delay for transportation to the unit, the first waiting patient from the queue seized the bed.

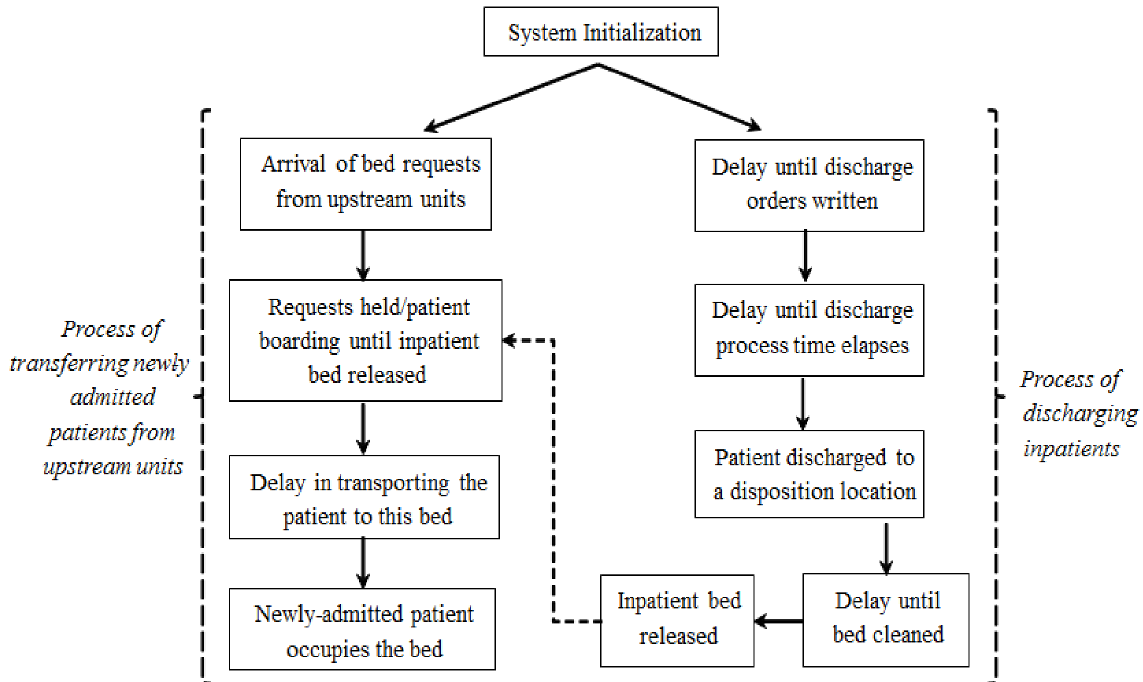


Figure 3-1: Conceptual Diagram of the Simulation Model

To model a specific n-by-T strategy, we modified the validated simulation model such that the flow of the first n patients (among those who are to be discharged that day) was altered, and those patients were simply assigned a discharge completion time (hour of day) with a triangular distribution; e.g., if T = 10 a.m., then Triangular(8, 9, 10) hr, and if T = 12 noon, then Triangular(9, 10.5, 12) hr. By changing the number of extra beds available at midnight to model the occupancy rate of the unit (e.g., 85% occupancy means approximately 18 of 21 beds occupied; i.e., 3 extra beds available at the start of the day), we were able to evaluate the impact of the variants of *n*-by-*T* on completion and boarding times under different levels of unit occupancy.

We used AnyLogic v7.2 (The AnyLogic Company, St. Petersburg, Russian Federation) to develop the discrete-event simulation model. The model was validated individually via face validation by the research team and KMC personnel, and via external validation by statistically comparing if the simulated values reasonably matched KMC's data (Eddy et al., 2012).

3.2.5 Phase 2: Pilot Implementation at the Unit

The promising results derived from the simulation of the *n*-by-*T* strategy in Phase 1 (discussed in the Results section 3.3) encouraged the hospital to implement a pilot of one of the variants, the 2-by-12 strategy, in their trauma unit. The pilot period was between June and December of 2014. This pilot was meant to identify requirements for a structured implementation study to be conducted later. Essentially, the unit nurse tried to work with her nursing staff in order to identify 2 patients at the beginning of their shift (usually 7 a.m.) and make an effort to get the attending surgeons to sign off on the discharge orders immediately. That would leave them 2-3 hours to finish the discharge processes relevant to those 2 patients in an effort to discharge them by 12 p.m. (noon). This was not possible every day owing to several reasons (discussed later in the Discussion section 0). We were provided with the implementation data for analysis by the unit staff. Statistical tests were used to compare the actual outcome measures for the days on which the target strategy was successfully implemented with those prior to the implementation period (Jan-May, 2014).

3.3 Results

3.3.1 Phase 1: Modeling the Current System

We first analyzed the current discharge process at the trauma unit. We were provided with 1789 unique patient records for the year 2013, out of which 1604 records had all the relevant data elements for our study. Figure 3-2 displays the following two phenomena: 1) for patients who are discharged on a given day, the corresponding distribution of order writing times and inpatient discharge times by hour of day, and 2) the arrival rate of inpatient bed requests from upstream units. Note that writing of discharge orders starts in the morning and often leads into the afternoon, a trend that is likely to exist in many trauma or surgical units. Consequently, the beds also get released throughout the day; the discharge completion time at this unit occurred during late afternoon (mean, 16.2 hr; median, 16.27 hr). The resulting mean boarding for upstream patients arriving throughout the day was calculated from the actual data as 2.41 hr (median, 1.63; s.d., 2.16). We also noticed that the discharge process length distribution was not identical throughout the day and depended heavily on when the physician wrote the discharge order; long for mornings and short for later than 3 p.m. Considering the schedules before and after 7 a.m. (shift change), the transportation time from the upstream unit to the inpatient unit was modeled as TRI(0.25,1.5,6.0) and TRI(0.25,0.75,4.0) hrs, respectively. The simulation model, which used inputs based on the actual data at the trauma unit (Table 3-1) to emulate the current system, was able to capture the complex dynamics of the inpatient unit reasonably well based on discharge completion and boarding time statistics (Table 3-2).

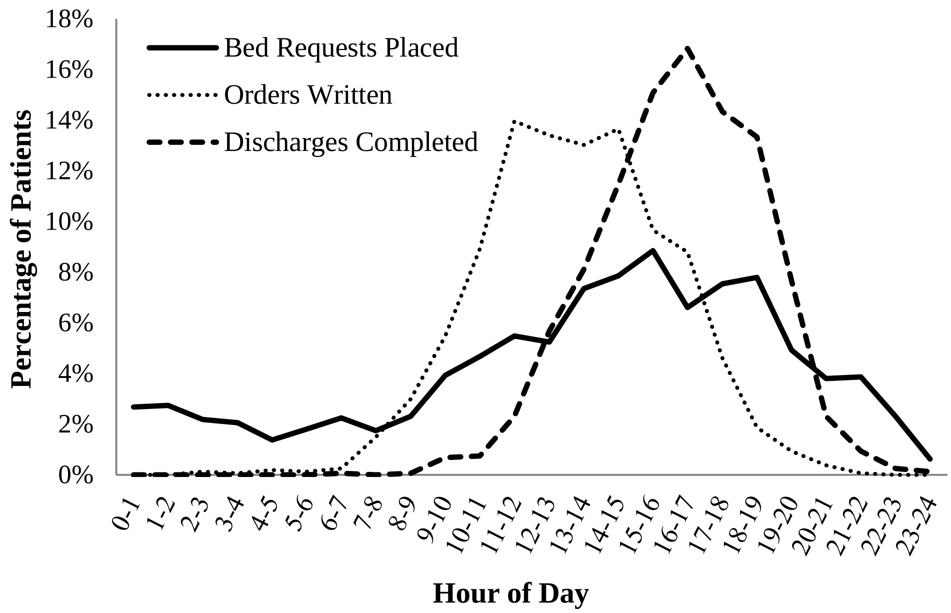


Figure 3-2: Discharge Process at the Trauma Unit in 2013

Table 3-1: Summary of the Data Used in the Model

Model Input	**Distribution**
Number of patients to be discharged (per day)	Poisson(4.39)
Time discharge orders placed (hour of day)	Normal(13.26, 2.68)
Discharge process length before noon (hours) between noon and 3 p.m. (hours) after 3 p.m. (hours)	 Weibull(4.64, 1.88) Weibull(3.03, 1.97) Weibull(2.07, 1.88)
Bed cleanup duration (hours)	Normal(1.51, 0.12)
Arrival of bed requests from upstream units	Non-stationary Poisson process; avg 4.39
Baseline occupancy rate	85% (18 of 21 beds)

Table 3-2: Validation of the Simulation Model against Actual Data from the Trauma Unit

Outcome	**Measure**	**Trauma Unit**	
		KHN (Actual) Data	Simulation
Discharge Completion Time	N (Patients/Days)	1604/365	4417/1000
	Mean (hr)	16.198	16.163
	Median (hr)	16.27	16.27
	Std Deviation (hr)	2.34	2.52
	Skewness	-0.23	-0.23
	95% CI on Mean (hr)	[16.08,16.31]	[16.09,16.24]
Boarding Time	N (Patients/Days)	1604/365	4268/1000
	Mean (hr)	2.41	2.35
	Median (hr)	1.63	1.86
	Std Deviation (hr)	2.16	1.82
	Skewness	2.07	2.14
	95% CI on Mean (hr)	[2.30,2.52]	[2.29,2.40]

3.3.2 Phase 1: Modeling the Effects of *n*-by-*T*

We next captured the distributions of discharge completion time generated by several specific instances of the *n*-by-*T* strategy using the validated simulation model (Figure 3-3). Note that *n* patients were guaranteed to be discharged prior to the set time each day, essentially resulting in a different distribution for these patients compared to the rest. This is evident from the switch in discharge completion time distribution from unimodal (as observed in the current unit) to bimodal. Notice that the peaks in the distributions for when n=1 and n=2 are different, and that only a marginal change was observed when T changed for a given n. That is, the mean completion times for cases when n=1 and n=2 (10 a.m. $\leq T \leq$ noon) were in the ranges 14.59–14.82 hr and 13.03–13.48 hr, respectively; an advancement of 1.38–1.61 hr and 2.72–3.17 hr when compared to the mean of 16.2 hr for the current strategy. Figure 3-4 depicts this in terms of hours advanced in the mean discharge completion times. The mean boarding times were around 2.13 hr and 2.04 hr, a reduction of 11.6% and 15.4%, respectively, over the current strategy (mean of 2.41 hr). While these benefits were reasonably high, they remained relatively unaltered irrespective of the value of *T* (between 10 a.m. and noon) because the mean discharge completion times changed very little during this time-frame.

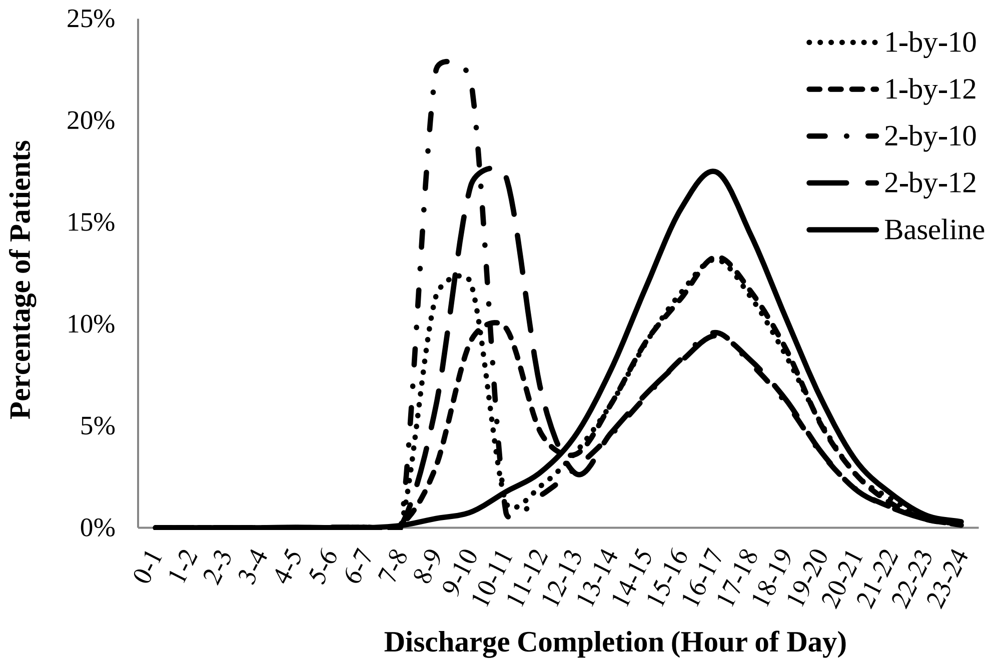


Figure 3-3: The Bimodal Distribution of Discharge Completion Times for Various *n*-by-*T* Strategies

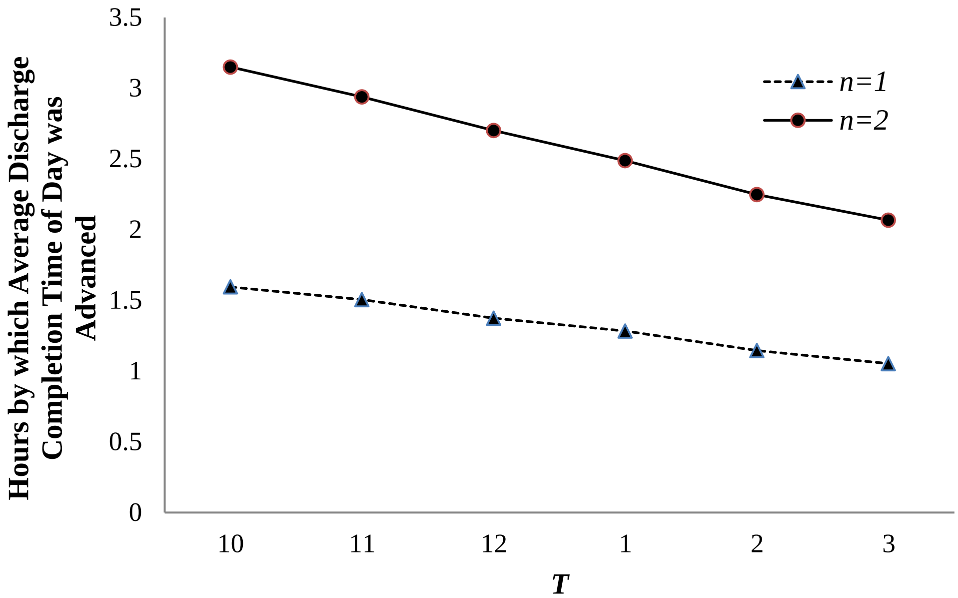


Figure 3-4: Effect of *n* and *T* on Advancement in Mean Discharge Completion Time

We also estimated an increase in annual inpatient bed hours due to advancement in the mean discharge completion time. Based on the annual 1789 discharges per year at this unit, the 1-by-*T* strategies (10 a.m. ≤ *T* ≤ noon) suggested an increase in 2469-2880 inpatient bed hours annually (corresponding to the advancement in the mean discharge completion times); this number increased to 4866–5671 bed hours with 2-by-*T* strategies. The corresponding increases in the upstream bed hours were nearly 500-662 hours annually for these two sets of strategies.

3.3.3 Phase 1: Modeling the Robustness of *n*-by-*T* to Occupancy Rate

While the above results corresponded to the unit's mean occupancy rate of 85%, the unit managers indicated that it varied throughout the year with some weeks nearing 100%. We, therefore, evaluated how occupancy rate of the unit would impact the performance of the *n*-by-*T* strategy (in particular, the 2-by-*T* of specific interest to the unit). Intuitively, changes in the occupancy rate (availability of empty beds at midnight) directly affect the rate at which new bed requests occupy empty inpatient beds (hence, boarding time) and does not affect the inpatient process to discharge patients (and thus mean discharge completion time) for a given n-by-T strategy. Table 3-3 shows the changes in the boarding times for occupancy rates ranging between 80% and 100%, for both 2-by-10 and 2-by-12 strategies. While 2-by-12 already would offer over 12% in boarding time reduction compared to the current system at 85% occupancy, this relative reduction would double (26.1%) during days (or weeks) when the unit experiences 100% occupancy; the corresponding upstream bed hours increased from 519 to 3238 hours.

Table 3-3: Reduction in Boarding Times Via 2-by-T Strategies for Various Occupancy Rates

Outcome	**Occupancy Rate**														
	100%			**95%**			**90%**			**85%**			**80%**		
	Baseline	T = 10	T = 12	Baseline	T = 10	T = 12	Baseline	T = 10	T = 12	Baseline	T = 10	T = 12	Baseline	T = 10	T = 12
Mean boarding time (hr)	6.91	4.94	5.10	4.42	3.16	3.25	3.03	2.40	2.44	2.34	2.04	2.05	2.02	1.89	1.90
% reduction	---	28.5%	26.1%	---	28.5%	25.4%	---	20.8%	19.4%	---	12.8%	12.4%	---	6.3%	6.0%
Increase in annual upstream bed hours	---	3524	3238	---	2254	2093	---	1127	1055	---	536	519	---	232	214

3.3.4 Phase 2: Analysis of Pilot Implementation

The above findings encouraged the hospital to conduct a pilot implementation of the 2-by-12 strategy in the same trauma unit during June-Dec 2014. Figure 3-5 indicates that the total weekly discharges by noon collected from the hospital's electronic health record increased by 2.4 discharges/week during the pilot when compared to the pre-implementation phase (152 days). A deeper analysis of the pilot data revealed that the unit experienced 2-by-12 only 12.67% of the total days (27 out of 213 days). Table 3-4 summarizes the outcomes for only those 27 days of successful pilot implementation compared to the pre-implementation outcomes. The distribution of the discharge completion times was found to be significantly different than that realized during the pre-implementation stage (p-value < 0.0001; Kolmogorov-Smirnov test); the strategy advanced the mean discharge completion time by nearly 2 hours per patient. Further, mean boarding time was also found to be significantly lower (p-value = 0.0269; Kolmogorov-Smirnov test); the strategy reduced boarding time by nearly 15%.

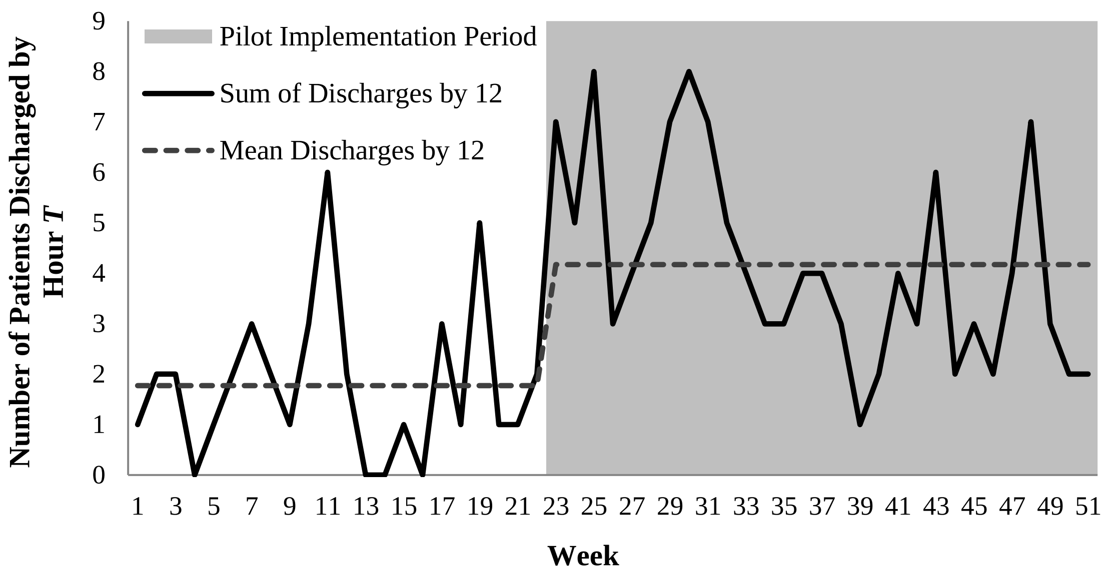


Figure 3-5: Total Weekly Discharges by Noon during the Pre- and Pilot-Implementation at the Trauma Unit in 2014 (Note: dotted line indicates mean of the weekly discharges during pre- and pilot-implementation)

Table 3-4: Comparison of Outcomes from Pre-Implementation and Pilot Study

		N	Mean (S.D.)	95% CI on Mean	Median (IQR)	*p*-value (K-S Test)
Discharge Completion Hour of Day (of inpatients)	Pre	746	16.30 (2.38)	[16.13,16.47]	16.44 (3.25)	-----
	Pilot	178	14.32 (3.48)	[13.81, 14.84]	14.68 (5.09)	< 0.0001
Boarding Time in Hours (of upstream patients)	Pre	719	2.36 (2.21)	[2.19, 2.52]	1.58 (2.03)	-----
	Pilot	138	2.01 (2.35)	[1.62, 2.41]	1.28 (1.15)	0.0269

3.4 Discussion

With inpatient flow pathways greatly impacting hospital operations and unnecessary delays, care coordination between intra-organizational operations and units becomes critical. In particular, the daily discharge of inpatients, a multi-step process, requires strong coordination among care providers in the unit (e.g., physicians, nurses, social workers, and case managers) and supporting processes and technology, while accounting for patient-specific factors, with implications on care quality, safety, and cost (Anthony et al., 2005; Farris et al., 2010). We noticed through job shadowing at a trauma unit that physician order writing times and discharge process durations were largely responsible for delays at that unit. Althought literature suggested that discharge timing of inpatients affects upstream boarding, no known approaches were available to suggest how best to advance the discharges. To this extent, we proposed a novel n-by-T target strategy that care providers could aim for every day, resulting in both advancing of dischage completion times and reducing boarding times. In particular, the 2-by-10 and 2-by-12 strategies were of special interest to this hospital. These strategies were considered during a pilot implementation, which confirmed the benefits (mean discharge time advanced by 2 hours and boarding reduced by 14.5%). Clearly, a target strategy such as the *n*-by-*T* provides a clear and easy guidance to the care providers in order to execute prompt release of inpatient beds for patients waiting upstream.

Our findings corroborate with previous research that focuses on inpatient discharge planning. In particular, we noticed a strong relationship between rising hospital occupancy and increasing ED length of stay (Forster et al., 2003). We noticed that as the trauma unit became busier (i.e., occupancy rate increased), the benefits from the *n*-by-*T* strategy became more prominent (ranging from 6-28%). During a 100% occupancy rate, no empty beds would be available in the inpatient unit for the first few bed requests that arrived between midnight and mid-morning (say 9 a.m.), causing them to accrue significant boarding. For less than 100% rates, there would always be one or more empty beds, minimizing boarding of the first few bed requests. We further confirmed previous observations that shifting the discharge distribution curve earlier in the day could mitigate ED boarding (Powell et al., 2012; Ozen et al., 2014). The resulting bimodal distribution of the discharge times, which is intuitive, caused the mean distribution time to shift towards the early part of the day (often by over 2 hours). The benefits of the *n*-by-*T* strategy on increasing the capacity-based measures (i.e., availability of inpatient and upstream bed hours) are worth noting. An increase in the number of inpatient bed hours can be significant, as these high-in-demand and expensive beds would now be available to schedule additional patients (e.g., electives or transfers). Similarly, an increase in the bed hours at upstream units (e.g., ED, ICU, PACU) means patients in those units no longer occupy such beds for unnecessarily long time. This means a reduction in waiting or crowding at these units. In some sense, the proposed *n*-by-*T* target discharge strategies allow for prompt release of medically-ready patients, making way for sicker patients in the upstream waiting.

The pilot confirmed findings of the simulation model in terms of both advancing discharges and reducing boarding times. The nursing manager noticed that while the 2-by-12 target strategy helped, to some degree, avoid a rush in the afternoon to execute planned discharges, it also gave her the ability to better schedule her nurses during the day, potentially avoiding costly overtimes. We also noticed that during pre-implementation only 4.16% of all patients were discharged by 12 noon based on the actual data from the unit; it increased to 29.78% for 2-by-12, clearly indicating the impact of these target strategies.

Although the benefits were clear, the challenges during implementation could not be overlooked. First, identifying the two patients to be discharged earlier in the day could be challenging. This unit ran a daily nursing huddle, so the nurses knew for the most part who were likely to be discharged the following day and what activities would be involved. However, recording this diligently every day and helping the involved nurse to coordinate with the physician, social worker, consulting physician, and other support services the following morning could be challenging. We noticed that timely completion on behalf of the consulting physician was especially challenging. Second, the disposition type could lead to difficulties in the inpatient emptying the bed in a timely manner (e.g., delays from family member to pick up the inpatient, or unexpected delays from insurance company on pre-certifications). Finally, nurses in the unit expressed a desire for continuous feedback that would enable them to evaluate their performance each day in light of the target and show improvements over the original unit. Provision of appropriate training and education to all providers in the unit, along with an appropriate system to continuously monitor the status of the unit, would help mitigate some of these problems and increase daily compliance to a specific *n*-by-*T* strategy for consistent benefits. Further, during high unit occupancy, even though literature suggests that individuals tend to speed up their processing, the possible necessity of additional staffing and the resulting cost implications should be considered carefully against the benefits of implementing this target strategy. The low compliance rate during the pilot can also be attributed to the fact that the pilot was conducted in a semi-structured manner, with little involvement from our engineering team. Given the low compliance rate during the pilot, we conducted post-hoc analysis by incorporating a compliance factor in our model. This factor randomly determined if a given day (in the simulation run of 1000 days) would be *n*-by-*T* compliant or not. Although not shown, we found that as the compliance rate decreased from 100% to 0%, the benefits (in terms of boarding time reduction and completion time advancement) of the proposed *n*-by-*T* strategy (in particular, 2-by-10 and 2-by-12) decreased nearly linearly. Both these measures approached values corresponding to the current system at 0% compliance.

Our research study design and findings, however, must be viewed in light of the following limitations. First, we assumed an average day for our modeling purposes. However, our model can easily incorporate trends and seasonalities corresponding to a specific day of the week, week of the month, or even month of the year. Second, we assumed that newly admitted patients will be transferred to the inpatient trauma unit using a first-come-first-serve queuing discpline. However, this may not be the case if certain patients may have to be fast-tracked to the inpatient beds. Third, the limited data did not allow us to incorporate and subsequently evaluate the effects of the support service processes. Fourth, the unavailability of daily occupancy rates did not aid us in establishing 1) if the number of patients to be disharged on a given day was correlated to the unit's occupancy rate, or 2) if the discharge process times were truly dependent on the time-of-day or based on another system state (current load or congestion). Fifth, we assumed in the model that all other medically-ready patients to be discharged on a given day, but not part of the *n*-by-*T* strategy, will continue to experience processes and times similar to the current system. Finally, we focused on a trauma unit, a specialized inpatient unit at the hospital. The generalizability of our findings would need to be evaluated across both medical and surgical units across geographically disparate hospitals.

Our study was both confirmatory and exploratory. We confirmed previous findings that the completion time of inpatient discharges has an impact on the boarding of patients being admitted from upstream units. We explored the impact of the proposed *n*-by-*T* strategy as a clear target for providers in the unit to better plan and execute daily discharges. This strategy, in some sense, is a combination of early order writing and shorter discharge process times on a select set of patients in an effort to release inpatient beds earlier in the day. This was shown through our experiments and via a pilot implementation to mitigate upstream boarding. Other perceived benefits of the pilot, but not recorded and quantified, included reduction in discharge delays and improved bed utilization at both upstream and inpatient units.

4 EVALUATING THE GENERALIZABILITY OF AN APPROACH TO IMPROVE THE INPATIENT DAY-OF-DISCHARGE PROCESS*

4.1 Introduction

Emergency departments (EDs) in the US are becoming increasingly common as general access points for acute care admissions. Consequently, ED boarding (patients waiting in the ED for inpatient beds) and crowding are becoming more apparent and impactful problems. Several studies have suggested that improving the inpatient discharge process to better balance discharges with admissions can alleviate ED capacity issues (M. Vermeulen et al., 2009; Kravet et al., 2007, Yancer et al., 2006).

As demonstrated in Figure 4-1, on a typical day in an inpatient unit, requests for beds in the unit arrive from multiple upstream sources. Most beds in the unit are occupied by inpatients; thus, in order for an incoming bed request to be fulfilled, a discharge must occur to free up an inpatient bed. The unit will typically have a few patients already identified to be discharged on this day (referred to as the day-of-discharge). For each of these patients, multiple processes must be completed, such as a discharge order placement by their physician, discharge instructions communication, and medications fulfillment. Upon completion of the discharge, the bed and room must be cleaned by hospital environmental services before the bed can be occupied by an incoming patient. Thus, it is apparent that discharge efficiency is critical, not only for patients to be

*Ballester, N., Parikh, P. J., & Peck, J. (2017). Evaluating the generalizability of an approach to improve the inpatient day-of-discharge process. In K. Coperich, E. Cudney, & H. Nembhard (Eds.), *Proceedings of the 2017 Industrial and Systems Engineering Research Conference*. Pittsburgh, PA: Institute of Industrial and Systems Engineers.

discharged but also for patients waiting in upstream units.

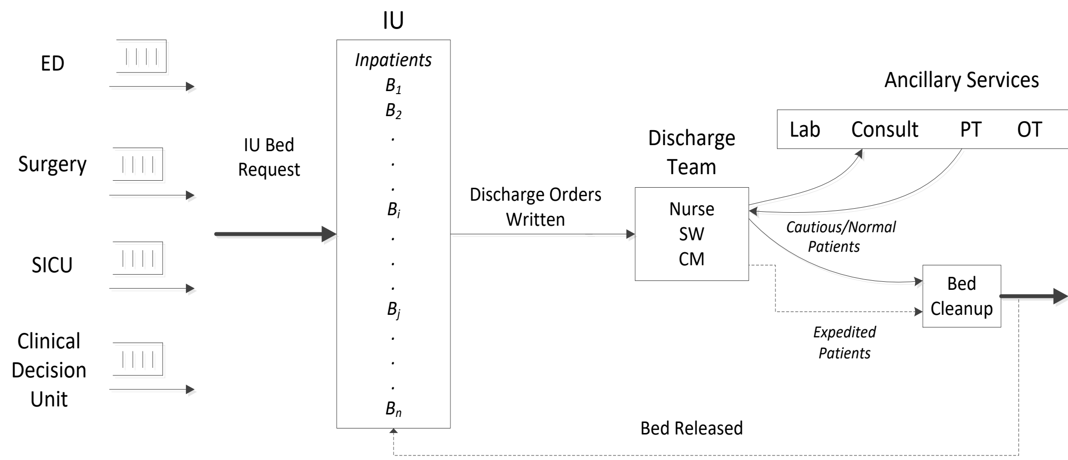


Figure 4-1: Schematic of an Inpatient Discharge Process

A few studies exist that examine analytical methods to evaluate inpatient discharge strategies and their potential effects on inpatient units and upstream patient boarding. Wong et al. (2010) built a system dynamics simulation model which suggested that smoothing out inpatient discharges over the course of a week reduces the number of ED beds occupied by general internal medicine inpatients and also reduces ED length of stay (LOS). Powell et al. (2012) used a simplified spreadsheet-based daily model and demonstrated that better timing of discharges should substantially reduce admitted patient boarding (across ED, elective surgery, and ICU transfers). Ozen et al. (2014) constructed a hospital-wide simulation model and found that prioritizing discharges in units with longer admission queues offered the most reduction in patients waiting to be admitted, rather than focusing on earlier discharges across all units. Matis et al. (2015) developed an optimization model, along with a proposed discharge process redesign, to determine an optimal discharge target time for each patient on a unit, given both patient and system centric constraints. Parikh et al. (2017) recently proposed a novel day-of-discharge strategy, *n*-by-*T*, as a target for inpatient units to advance discharge completion times and reduce upstream boarding. This strategy was initially tested using a simulation model and later pilot at a trauma inpatient unit at a local hospital in the Midwest US.

In this paper, we address the following questions*: (i) Could a recently proposed model for the inpatient discharge process be generalized to units at other hospitals? and (ii) Would the n-by-T strategy offer similar benefits at those units?* We consider a Neurology inpatient unit at a hospital in the Northeast US to address the above questions. We first briefly summarize the general (conceptual) model (presented in Parikh et al. (2017)) to capture the relationship between inpatient discharges and upstream patient boarding (Section 4.2), following by a discussion of its application at this Neurology unit and the evaluation of the *n*-by-*T* strategy (Sections 4.3 and 4.4).

4.2 A General Model for the Day-of-Discharge Process

Although the typical day on an inpatient unit is quite complex, the processes associated with discharges for that day and the corresponding new admissions can be viewed, in the general sense, as two separate streams (discharge ready patients and bed request arrivals), linked by the resource of inpatient beds, as demonstrated in Figure 4-2.

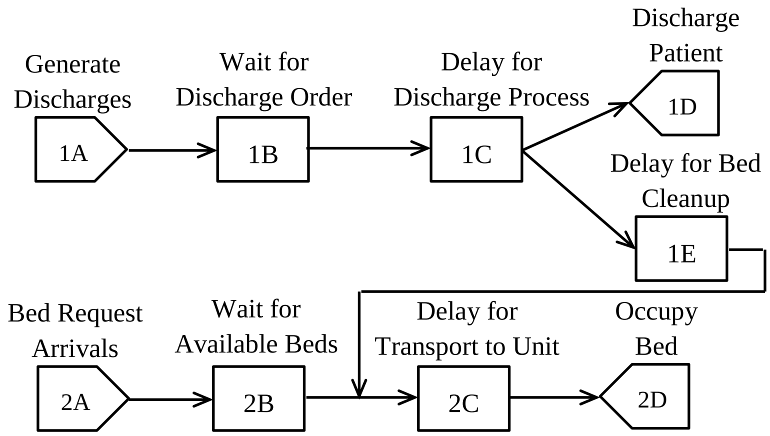


Figure 4-2: Schematic of the General Model

The first stream, the number of patients (entities) to be discharged (block 1A), depends on the unit's daily discharge rate. These patients when discharged at the end of the day will empty the beds they are currently occupying. Depending on the occupancy rate in the unit, it may be important to make available additional empty beds at the start of the day; 0 if 100% occupancy. In a typical unit, discharge-ready patients wait until their discharge order is placed (block 1B), after which they are delayed for some discharge process length (block 1C). After this, the patients are discharged (block 1D) releasing the beds they had occupied, which would need cleaning before the bed becomes available (block 1E).

The second stream, the patients requesting a bed, are generated throughout the day based on the unit-specific arrival process (block 2A). These requests enter a queue of beds (block 2B). Once a bed becomes available, a requesting patient in the queue (based on FIFO or priority) would experience a transportation delay (block 2C) before reaching the room and occupying the empty bed (block 2D).

This general model requires inputs for the following: (i) number of discharges per day (block 1A); (ii) discharge order placement times (block 1B); (iii) discharge process lengths (block 1C); (iv) bed cleanup delays (block 1E); (v) bed request arrival times (block 2A); (vi) transport to unit delays (block 2C). The outputs of the model are (i) discharge completion times of day (block 1D); (ii) upstream patient boarding times (difference between block 2A and block 2D). Note that the boarding time includes transportation delay, often the way a unit records it; the true boarding (waiting time) would exclude this transportation delay.

This general model makes several assumptions: all processes associated with the discharge are combined into one delay; discharge order placement is used as a proxy for discharge initiation; the model delays for bed cleanup and for transport incorporate both the time spent waiting for these services to arrive and the actual service time. However, as shown by Parikh et al. (2017) and as we show below, these assumptions appear reasonable to capture the critical dynamics in the unit. We embedded this general model in a simulation framework in AnyLogic v7.2.

4.3 Application of the General Model to a Neurology Unit

We now discuss the application of this general model to the Neurology unit in the Northeast US to obtain evidence of the generalizability of it beyond the Trauma unit in Midwest US. The key differences observed in the Neurology unit (vs. Trauma) are as follows: (i) there are 26 inpatient beds (vs. 21) with an average discharge time of day of 2 p.m. (vs. 4 p.m.); (ii) the average upstream boarding was 3.53 hr (vs 2.41 hr) and the rate of discharges was 3.57 patients/day (vs 4.91). So clearly, besides patient populations, the values of the system variables are disparate.

The above data for the Neurology unit was obtained after 30 hours in job shadowing unit nurses and obtaining a year’s worth of retrospective data for all patients discharged from the unit in 2015. For these patients, we obtained four date-time stamps from the electronic health records: (i) bed request placed; (ii) in room time; (iii) discharge order placed; and (iv) discharge completion time. Although these four time stamps were specific to the same patient encounter, we considered the arrival data independently of the discharge data in our analysis and subsequent model.

For each patient, we considered the bed request and in room times for only the first time the patient arrived on the unit; if the patient was temporarily transferred to other units throughout their course of treatment and then returned to the Neurology unit, we did not use the bed request and in room times when they returned to the unit, as we were modeling only new incoming demand for unit capacity. We only considered records for patients who were eventually discharged out of the hospital from the Neurology unit. We excluded records with missing values and records with chronologically inconsistent data (in room time occurring before bed request placed, or discharge completed before order placed). Because we modeled only the day of patient's discharge, the length of stay was not considered. Additionally, we only considered records for patients who arrived in the room the same day their bed request was placed and patients who were discharged the same day their discharge order was written. Figure 4-3 summarizes the bed request arrivals, discharge order placements, and discharge completion times from this final dataset, by hour of day over 1303 records.

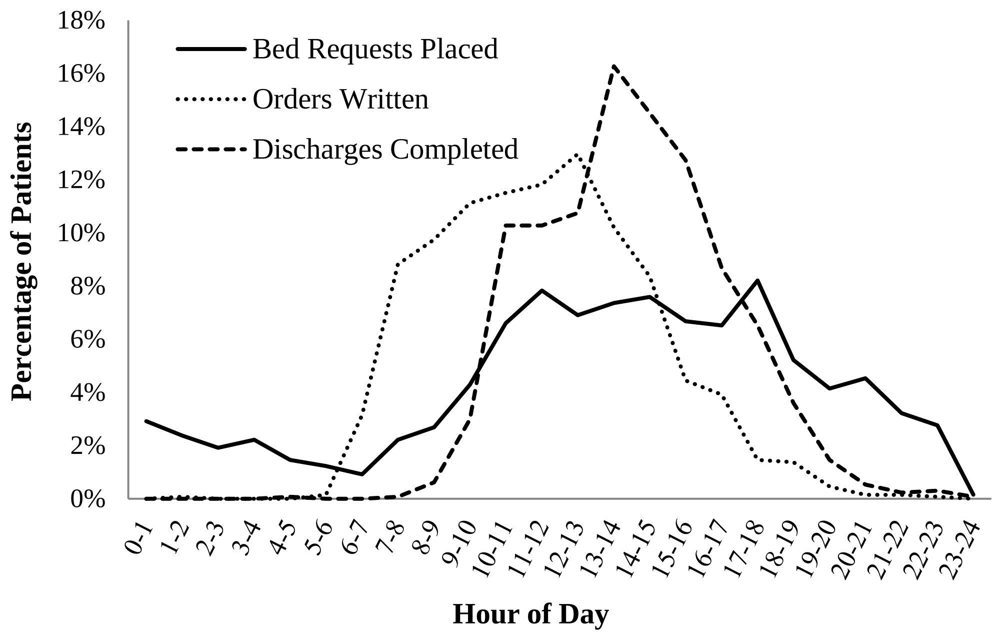


Figure 4-3: Bed Requests and Discharges at the Neurology Unit in 2015

From the four time stamps provided in the dataset, we derived input distributions for the model for the following four inputs: (i) number of patients discharged per day; (ii) discharge order writing time of day; (iii) discharge process length (the difference between discharge order placed and discharge complete); (iv) bed request arrival time of day. Unfortunately, we were unable to obtain any data directly for bed cleanup times; for these, we relied upon expert estimates and simulation model feedback. Likewise, for transportation to the unit times, we had only sparse, incomplete data, so we relied upon a combination of this data and simulation model validation feedback to derive appropriate distributions. Because of the difficulty in quantifying the unit's daily occupancy rate due to ongoing room renovations and temporary bed unavailability, we assumed 1 extra empty bed at the start of a day.

Table 4-1 summarizes the final input distributions corresponding to the Neurology unit. We observed multiple instances of non-stationary processes (by time of day) at this unit. Such processes were often longer (larger means, longer tails) the earlier they occurred in the day, indicating perhaps that units are typically busier in the mornings catching up with work accumulated from overnight, or else there is less of a focus on discharges in the morning.

Table 4-1: Model Inputs Derived from the Neurology Unit Data in 2015

Model Input	**Distribution**
Number of patients to be discharged (per day)	Poisson(3.57)
Time discharge orders placed (hour of day)	Normal 2 Mixture: Normal(8.27,0.99); probability 0.19 Normal(12.32,2.66); probability 0.81
Discharge process length before 10 a.m. (hours) between 10 a.m. and 4 p.m. (hours) after 4 p.m. (hours)	 Weibull(3.998,1.75) Weibull(2.21,1.52) Weibull(1.24,1.73)
Bed cleanup duration (hours)	Normal(1.51, 0.12)
Arrival of bed requests from upstream units	Non-stationary Poisson process (rate varies by hour of day); daily avg 3.57
Transportation to unit length before 7 a.m. (hours) between 7 a.m. and 7 p.m. (hours) after 7 p.m. (hours)	 Triangular(0.34,0.86,1.7) Triangular(0.16,1.49,4.46) Triangular(0.16,0.83,2.15)
Number of empty extra beds at start of day	Constant = 1

We averaged our simulation findings over 1,000 replications (of a 24-hour day-of-discharge on the unit). For validation, we compared the simulation outputs against the unit's actual data: on the inpatient discharge side, discharge completion time of day; on the upstream bed request side, patient boarding time (length). As shown in Table 4-2, our simulation model output reasonably matched our retrospective unit data for both validation measures, across multiple statistical measures.

Table 4-2: Model Validation against Data from the Neurology Unit

Outcome	Measure	Actual Data	Simulation
Discharge Completion Time of Day	N (Patients/Days)	1303/365	3608/1000
	Mean (hr)	13.99	14.01
	Median (hr)	13.92	13.90
	Std Deviation (hr)	2.54	2.75
	Skewness	0.27	0.09
	95% CI on Mean (hr)	[13.85,14.13]	[13.92,14.10]
Boarding Time	N (Patients/Days)	1303/365	3500/1000
	Mean (hr)	3.53	3.74
	Median (hr)	2.60	2.58
	Std Deviation (hr)	2.90	3.36
	Skewness	1.84	1.76
	95% CI on Mean (hr)	[3.37,3.69]	[3.63,3.85]

Clearly, the general model (summarized in Section 4.2) seems to fairly accurately model the Neurology unit's day-of-discharge process. This is now the second, distinct, unit where such a general model was validated, the first being the Trauma Unit (Parikh et al., 2017). The two successful validations of the general model across differing units indicate that, while a unit-specific model can capture detailed dynamics, the majority of the inpatient unit admission and discharge process dynamics may be common across units and could be modeled in a unit-independent framework to generalize findings.

4.4 Generalizability of the *n*-by-*T* Target Discharge Strategy

The second research question was if the previously proposed *n*-by-*T* target inpatient discharge strategy (Parikh et al., 2017) would benefit the Neurology unit as well. Essentially, the *n*-by-*T* strategy proposes a target number of patients, *n*, to be discharged from the unit by a target time of day, *T*. These *n* patients are to be selected by the unit from among the patients already identified as ready to be discharged on this particular day. In a sense, this strategy is a hybrid of two separate strategies considered earlier; advancement in discharge order writing time and reduction in discharge process length. The key benefit of the *n*-by-*T* strategy is that it offers the advantage of requiring order writing advancement and discharge process length reduction efforts for only a fraction of discharge-ready patients on a given day. This potentially avoids excessive workload on unit staff in the morning (working on all discharge-ready patients vs. a fraction of them), while still achieving the goal of better synchronization between discharges (bed availability) and upstream bed request arrivals (bed demand) via earlier discharges.

Figure 4-4 displays the expected effect of several specific instances of the *n*-by-*T* strategy on discharge completion times at the Neurology unit. The bimodal nature of the distribution of discharge completion times results from the *n* patients discharged earlier in the day, and the rest are discharged per the current process, though at a reduced volume. Note that while the distributions for *n*=1 and *n*=2 are different, there is only a marginal change when *T* changes for a given *n*, indicating that the number of patients is the critical factor to be decided when selecting a variant of *n*-by-*T* for the unit, rather than the time of day by which to discharge these patients.

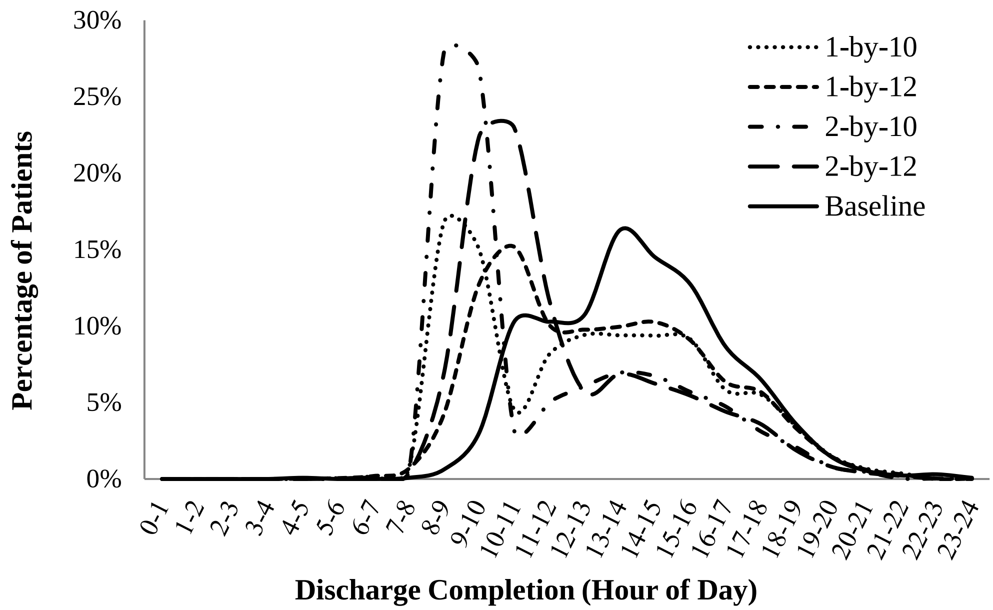


Figure 4-4: Discharge Completion Times for Various *n*-by-*T* Strategies

We quantified the estimated benefits of implementing the *n*-by-*T* strategy at the Neurology unit using four measures. For upstream patients, we calculated the percent reduction in average boarding time per patient; correspondingly, we calculated the estimated increase in upstream unit capacity in the form of annual upstream bed hours (based on 1303 discharges). For inpatient discharges, we calculated the percent advancement in average discharge completion time of day per patient; likewise, we calculated the corresponding estimated increase in inpatient unit capacity in the form of annual inpatient bed hours. These results are summarized in Table 4-3. The numbers displayed are the averages of 10 simulation runs of 1,000 replications each.

Table 4-3: Predicted Outcomes of *n*-by-*T* at the Neurology Unit

	% Reduction in Average Boarding Time per Patient		**Increase in Annual Upstream Bed Hours**		**% Advancement in Average Discharge Completion Time of Day per Patient**		**Increase in Annual Inpatient Bed Hours**	
	***n*=1**	***n*=2**	***n*=1**	***n*=2**	***n*=1**	***n*=2**	***n*=1**	***n*=2**
***T*=10**	7.59%	13.57%	349	624	9.58%	18.31%	1747	3338
***T*=11**	7.46%	12.70%	343	584	8.53%	16.38%	1555	2987
***T*=12**	5.60%	11.63%	258	535	7.55%	14.75%	1377	2688

It is apparent that, while all combinations of *n* and *T* experimented in our study offer improvements over the current system across all four metrics, *n* has much more of an effect than does *T*. Additionally, the most aggressive strategy, 2-by-10, results in the largest improvements in all four areas; intuitively, this is to be expected.

These conclusions were also found in the study at the Trauma unit (Parikh et al., 2017). The expected benefits due to *n*-by-*T* were larger at the Trauma unit, however ~11% for the 1-by-*T* strategies and ~15% for the 2-by-*T* strategies. This is possibly due to the higher patient volumes at the Trauma unit and/or their later peak discharge time of day. That study also identified several potential difficulties to successful implementation of *n*-by-*T*, such as identification of the *n* patients, timely completion by the consulting physician, disposition-specific complications, and the need for feedback, education, and sustainment. Such considerations would be vital if such a target strategy were to be implemented at the Neurology unit.

4.5 Discussion and Conclusion

The main contribution of this study was to obtain evidence of the generalizability of a proposed model for the inpatient day-of-discharge process. To do this, we considered a Neurology unit at a large hospital system in the Northeast US. Despite the differences between the units in the initial study and this current study (e.g., trauma vs neurology, geographical location, system parameters), we were able to successfully validate the general model at the Neurology unit as well by only altering the input distributions specific to the unit, without any change in the model's logic. This provides evidence that the model is robust and generalizable, as demonstrated across two different units in two different hospitals; however, we recommend further studies to verify this claim.

We also observed that the n-by-T target strategy would provide similar benefits to this Neurology unit as well. Although the expected boarding time reductions were not as large for this unit (e.g., for 2-by-noon, it was over 11% vs. 15% at the Trauma unit), the general conclusions remained the same: all combinations of n and T offer improvements over the current system across four different metrics, with more aggressive strategies offering the most improvements, and with n having a much larger effect on the expected benefits than T. This suggests that n-by-T may be an effective discharge target strategy for any unit in any hospital; again, further research at other units is recommended to truly generalize the benefits of this target strategy.

Future research in this area should consider the inclusion of the differences among the discharge-ready patients based on the underlying effort required by the unit staff to discharge them on that day, disposition location, and capacity limitations at care transition locations.

5 SEQUENCING DAILY PATIENT WORKLOAD FOR AN ANCILLARY SERVICE PROVIDER*

5.1 Introduction

Recent research suggests that an effective way to increase the efficiency of hospital patient flow is by better synchronizing inpatient discharges with upstream admissions (M. Vermeulen et al., 2009; Kravet et al., 2007; Yancer et al., 2006). Inefficient discharge planning can result in discharge delays that increase length of stay and contribute to upstream patient boarding and crowding, especially in the emergency department (ED).

Discharge planning in an inpatient setting involves a care team of individuals from various clinical services. Physicians and nurses are primarily involved with the clinical aspects of a patient's care, diagnosing health problems and determining treatment plans; therapists bridge the clinical and logistical gap, directing the patient's functional rehabilitation; and care management coordinates the logistics of the patient's payment and discharge. Table 5-1 summarizes the main decision points in discharge planning and the responsibilities of each service at those points which span from clinical to logistical.

The discharge planners in therapy and care management, commonly known as support or ancillary services, are critical but often constrained resources. Often there is just one full-time Physical Therapist (PT) and one Occupational Therapist (OT), one Registered Nurse (RN) and one Social Worker (SW) care manager assigned to an entire inpatient unit (IU) (with over 30 beds in the units observed during this study). This may cause bottlenecks in planning and executing a discharge, as these care providers are responsible for all patients on the unit, but they cannot only prioritize discharges at the expense of the other patients.

Table 5-1: Discharge Decision-Making

	Physicians/ Nurses	**Therapy (Physical, Occupational)**	**Care Management/ Social Work**
When	Is the patient clinically ready for discharge (from the perspective of their primary diagnosis)?	Is the patient ready for discharge (from the perspective of their activities of daily living and recovery of functionality)?	When is the patient's family available for pickup? When is a transportation service available for pickup? When does the destination facility have availability?
Where	Can the patient go home, pending therapy evaluation?	Should the patient go home or does s/he require rehabilitation care, whether via a facility or home services?	Which facilities/locations does the patient prefer? Which facilities will take the patient's insurance? Which facilities have availability?
How	What medication does the patient need? What is the patient's follow-up plan of treatment?	What equipment does the patient need?	What level of support can the patient's family and friends provide? How will the patient get transported to his/her destination? How will the patient pay for the care s/he needs?
	Clinical		Logistical

Despite the critical importance of therapists and care managers in discharge planning, they have received little attention from healthcare researchers. The vast majority of literature in discharge planning adopts either a unit or hospital perspective, or the viewpoint of the clinical providers, mainly physicians and nurses. Yet the decisions facing ancillary service providers on a day to day basis are no simple matter. For instance, consider a typical day on an inpatient unit for one ancillary service provider (ASP), as illustrated in Figure 5-1.

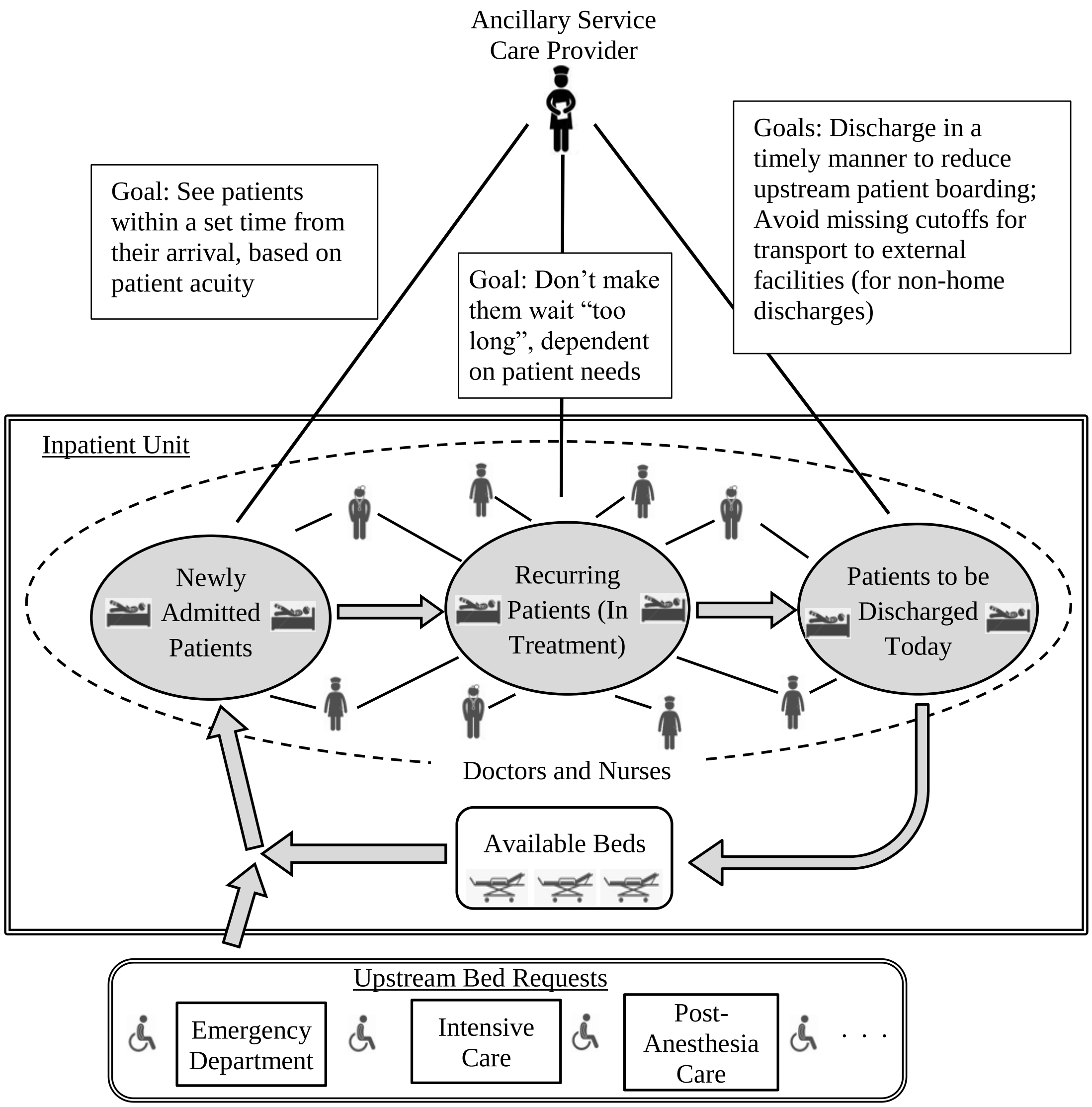


Figure 5-1: A Day on an Inpatient Unit for an Ancillary Service Provider (ASP)

Daily, an ASP has a set of patients to see, which may be categorized into three groups:

- Group D: *Discharge-ready* patients whose treatment is complete and discharge plans have been finalized.

- Group A: *Newly admitted* patients that have not yet been seen by the ASP either because they recently arrived on the unit and/or because orders for this ancillary service were recently placed.
- Group R: *Recurring* patients currently in treatment in the IU who will continue to be seen on a daily basis.

These three groups of patients have different characteristics and are associated with objectives that are often competing from the ASP's perspective. For Group D, the ASP would want to ensure that these patients are discharged in a timely manner to satisfy bed requests for patients waiting in upstream units. Additionally, some of these patients may have cutoff times if they are discharged to a non-home facility (often 3 p.m.). If the discharge processes are not accomplished by then, this patient would spend an additional, unnecessary night at the unit. Other activities such as attending physician's discharge order, laboratory tests/consults, and post-discharge care plan discussion by the RN are part of the overall discharge process of Group D patients.

For Group A (new patients), the inpatient unit may have policies that require the ASP to see a newly-admitted patient within a specified time (typically 24-48 hours) upon their admission to the unit. These patients require initial evaluation and assessment by the ASP. For Group R (the recurring patients), the ASP would have to see some of them early in the day if specific aspects of daily treatment of the patient's care depend upon the ASP's input or initiation (e.g., occupational therapists must fit spinal injury patients for a brace before they can move and begin physical therapy). The time required for these patients is variable (10 minutes to an hour as observed by the authors).

Each morning the ASP is faced with the following question: *how should I prioritize these patients so that everyone is seen today and all discharges are accomplished in a timely fashion?* The ASP's objective is to complete discharges (Group D) in a timely fashion while meeting the constraints of initial evaluation windows (Group A), avoiding care delays (Group R), and meeting discharge cutoffs (Group D). Figure 5-2 shows a potential scenario and associated possible solution (assuming a typical 8 a.m. start time to see patients, after completion of 7-8 a.m. patient hand overs, nursing huddles, and other administrative or educational duties).

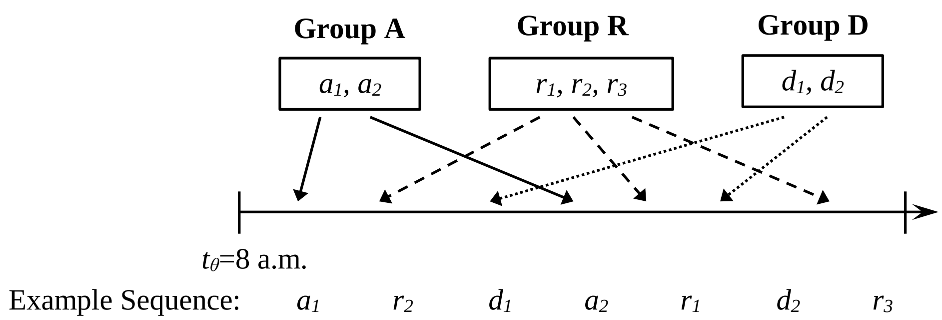


Figure 5-2: A Potential Workload Day for an Ancillary Service Provider

In this sequence, the ASP first sees a new patient (Group A), followed by a recurring patient (Group R), and finally a discharge patient (Group D), and repeats this cycle until all patients are seen. The choice of the group and a specific patient within it must be made in a way that satisfies temporal constraints. For instance, if the first discharge patient, d_1, is destined for a long-term care facility with an admission cutoff of 3 p.m., placing that patient earlier in the sequence would ensure meeting the cutoff; if the second discharge patient, d_2, is a home discharge with no associated cutoff time, then placing the patient later in the sequence would suffice. Likewise, the first newly admitted patient, a_1, and the second recurring patient, r_2, may have constraints (initial evaluation window for a_1, care requirements for r_2) that prevent them from being placed any later than they are in the sequence.

While the above illustration provides a feasible sequence for the ASP across these 7 patients, it is not easy to derive an optimal sequence in a real setting across 20+ patients (a typical ASP patient workload observed by the authors). Clearly, balancing an ASP's workload in a way that maximizes discharge efficiency, while meeting requirements due to logistics of care and hospital policies, is no simple matter. To address this challenging and practical issue faced by ancillary service providers, we pose the following question: *How to derive an optimal sequence of patients on a daily basis for an ancillary service provider assigned to an inpatient unit such that upstream patient boarding is minimized while adhering to care provision and transition constraints?*

The remainder of this paper is organized as follows. After reviewing the relevant literature, both in healthcare and operations research, in Section 5.2, we present our modeling approach to a typical workday for an ASP on an inpatient unit and a scenario-specific MIP formulation in Section 5.3. Section 5.4 discusses the use of our model in a scenario sampling based optimization approach and presents a simulated-annealing method for practical strategy derivation in an applied setting. Section 5.5 presents our experimental evaluation of our approach and comparison to other potential strategies. Section 5.6 concludes the paper and provides recommendations for future research.

5.2 Relevant Literature

5.2.1 Sequencing/Scheduling in Healthcare

The authors were unable to identify research specifically addressing sequencing daily patient workload for an ASP on an IU. However, sequencing and scheduling problems are not new to healthcare as a whole. We here summarize some of the more recent and relevant contributions.

In the inpatient setting, several studies consider the scheduling of patient appointments. Paulussen et al. (2006) develop an agent-based approach to inter-unit patient scheduling in hospitals. Chien et al. (2008) examine scheduling physical therapy rehabilitation operations, modeling their problem as a hybrid (job) shop scheduling problem and solving it with a genetic algorithm, benchmarking their solution with an MIP model.

Another area of interest is diagnostic resource capacity allocation. Patrick et al. (2008) examine the scheduling of patients with different priorities for a diagnostic resource (CT scanner). They model this scheduling problem as a Markov decision process and solve the equivalent linear program through approximate dynamic programming. More recently, Geng and Xie (2016) expand on this problem and propose a finite-horizon Markov decision process to determine optimal patient scheduling for such a diagnostic facility. I. Vermeulen et al. (2009) present an approach to optimization of resource calendars, using computer experiments to simulate different scheduling approaches for allocating CT-scan capacity to different patient groups.

Existing research also considers the staffing problem for various care providers in IUs and EDs. Jones and Evans (2008) develop an agent-based simulation model to evaluate the impact of various ED physician staffing schedule configurations on patient waiting time. Ogulata et al. (2008) propose a hierarchical mathematical model, tested on real data, to generate weekly staff schedules for a physiotherapy service in a hospital. This model selects patients for physiotherapy, assigns them among the available physiotherapists, and then schedules them throughout the day for each physiotherapist. Topaloglu and Selim (2010) present an application of fuzzy set theory to solve the nurse scheduling problem (generating individual schedules for nurses that consist of workdays and days off over a planning period spanning a number of weeks).

Surgical suite efficiency is another area in which scheduling of patients, staff, and capacity is crucial, and operating room (OR) scheduling is well studied in the literature. Cardoen et al. (1010) provide an extensive survey of research and methods for improving OR planning and scheduling. More recently, Mancilla and Storer (2013) propose a decomposition based approach to solve the stochastic sequencing of surgeries for a surgeon shared across two parallel operating rooms.

Multiple studies exist that focus on outpatient appointment scheduling. Guo *et al.* (2004) use discrete-event simulation to examine several scheduling rules to improve appointment scheduling in an outpatient clinic. Rohleder et al. (2011) use discrete-event simulation to evaluate alternative staffing levels and patient scheduling rules for an outpatient orthopedic clinic. Zeng et al. (2010) examine the outpatient scheduling problem with overbooking for patients with different no-show probabilities to maximize expected profit, including revenue from patients and costs associated with patient waiting times and physician overtime. They examine the properties of the objective function and optimal schedules, propose a local search algorithm and two sequential scheduling procedures, and perform numerical experiments to derive managerial insights.

The work closest to our research would be that of Ogulata et al. (2008), with the following key differences. *First*, they consider the allocation of patients among multiple providers in a physiotherapy service; we focus on a single, generic ancillary service provider on a single unit. *Second*, they do not consider upstream effects, rather seek to maximize the number of patients seen, equally distribute workload among providers, and minimize patient time waiting on the providers; we account for systemic effects by considering upstream boarding time. *Third*, they consider patients as a single group weighted by individual priorities for physiotherapy; we consider different types of patients such as newly admitted, in treatment, and to-be-discharged. *Finally*, they consider a deterministic setting; we consider a stochastic one.

5.2.2 Operations Research Applications

If we view the ASP as a machine and the patients to be seen on a given day as jobs, then the ASP patient sequencing problem is conceptually similar to the single machine sequencing problem with three key characteristics: (i) an objective (upstream patient boarding) which is not standard; (ii) multiple job groups (three groups of patients); and (iii) stochastic processing times (group-dependent).

Our problem contains different groups of jobs (patients). Scheduling problems with multiple types of jobs (typically referred to as job classes) on the same machine have been addressed in the literature. Potts (1991) proposes algorithms for minimizing completion times in a single-machine, multiple job class setting. Webster et al. (1998) develop a genetic algorithm to minimize lateness and earliness in the same setting (single machine, multiple job classes). However, the interest in these problems arises from the fact that a penalty is incurred when switching between different classes of jobs in the sequence; a whole branch of research dedicated to scheduling under setups exists, see Allahverdi et al. (2008) for details. In contrast, in our problem, the different job groups drive the objective function and constraints, and determine the stochastic distributions of the processing times, rather than incurring setups in the sequence. Consequently, we avoid referring to our job categories as classes, and instead refer to them as groups.

Stochastic sequencing problems are less studied than their deterministic counterparts, and vary in the solution methods. Researchers such as Sarin et al. (1991) and Zhou and Cai (1997) develop optimal sequencing rules for specific objectives for the stochastic single-machine problems. Van Oyen et al. (1999) follow a similar approach for a more complicated setting of the single-machine problem with due dates and job classes.

The ASP's patient sequencing problem has the following stochastic variables: (i) the processing time required of the ASP for each patient; (ii) the time required by the rest of the unit to fully complete a discharge; (iii) the arrival times of bed requests to the unit throughout the day. Note that while the number of patients to be seen in a given day is stochastic from day to day; it is known to the ASP at the start of the shift with a fair amount of certainty, which is the focus of our study.

5.3 An Optimization Model for ASP Sequencing

5.3.1 Characterizing a Typical ASP's Workday

We take a static-list single-machine sequencing approach to characterizing a typical workday of the ASP. We model all ASP-specific tasks associated with each patient as one single processing time for that patient. Once the ASP begins to see patients, the ASP continues to process patients in the specified order until all those on the list have been seen. We approach the ASP as a limited (bottleneck) resource on the unit and assume that other services adjust to the ASP's schedule so that there is no blocking for the ASP in fulfilling the sequence for the day. We assume that the patients to be seen today are all known in advance at the start of the ASP's shift and no new patients are added throughout the day. This is reasonable, as newly admitted patients arriving to the unit throughout the day typically need to be seen within 24 hours, so they could be considered as newly-arrived patients on the next day. We assume processing times are independent of each other and of the sequence. We model the initial evaluation windows for Group A patients and care needs of Group R patients as hard due dates by which they must be processed by the ASP, although these may be more flexible in practice.

Group D patients are not only processed by the ASP, but also require additional interactions with other care providers as part of their overall discharge process. We model this overall discharge process for each patient, excluding the ASP's contribution, as a single process on the day-of-discharge, calculated from midnight. In reality, this process is composed of various steps executed by different elements of the care team, along with periods of inactivity and patient waiting. Our approach is necessitated by the variability in this process, the paucity of data, and the fact that there is little to no standardization in the order in which these subprocesses occur. Discharges are processed in parallel by the unit; however, the ASP must see each one individually at some point before the patient can be discharged from the unit and the bed made available. We assume that it is reasonable for the ASP – the bottleneck service – to preempt the rest of the discharge process at any time (i.e., there are no precedence constraints between these two processes). Our approach to modeling a discharge can be visualized in Figure 5-3.

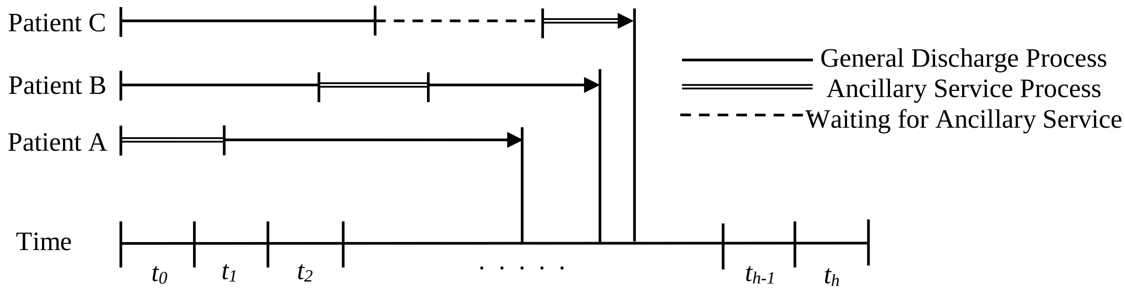


Figure 5-3: Modeling Convention for the Inpatient Discharge Process

As discussed previously, patients discharged to facilities have cutoff times by which they must be discharged to a facility or spend an extra night in the hospital. We model these as due dates by which the entire discharge must be completed, both the ASP-specific process and the remaining unit discharge process. To avoid confusion, we refer to these as discharge cutoff times rather than discharge due dates.

In building our model, we make the assumption that there are no empty beds in the unit (100% occupancy), as we only model the bed requests that depend upon discharges. Patients arriving to a unit with empty beds will experience no unit-dependent boarding time. For this reason, we also assume an equal number of bed requests and discharges. If the number of discharges is greater, the extra discharges will not affect the boarding time objective; if the number of bed requests is greater, the excess bed requests will never be fulfilled no matter what sequence is chosen.

5.3.2 A Scenario-Specific MIP Model

As indicated in Section 5.2.2, the ASP's patient sequencing problem is stochastic in nature. A scenario corresponds to the system state characterized by three random variates jointly drawn from the ASP processing time, discharge processing time, and bed request arrival time distributions, respectively. For ease of understanding, we now present the scenario-specific non-linear MIP model for optimal sequencing of patients with the objective of minimizing boarding time of upstream patients. Table 5-2 and Table 5-3 summarize the notations used in the model.

Table 5-2: Table of Notation

Parameter	Description
N	Set of patients to be seen by the ASP; $i, j, k \in N$
$D \subseteq N$	Set of patients to be discharged today; $d, d' \in D$
B	Set of upstream bed requests; $\lvert B \rvert = \lvert D \rvert$; $b \in B$
t_0	Start time of the first patient by the ASP (shift start after nursing huddle and/or rounds)
p_i	Processing time for patient *i* with the ASP
u_i	Due date for patient *i* to be seen (processed) by the ASP
ρ_d	Discharge processing time for patient d (sum of all processes required by providers other than the ASP for a discharge to be completed)
δ_d	Discharge due date for patient *d*
α_b	Arrival time of upstream bed request *b* (presorted in nondecreasing order)

Table 5-3: Table of Decision Variables

Decision Variable	Description
x_{ij}	Linear ordering variable; $\begin{cases} 1 & \text{if patient } i \text{ precedes patient } j \text{ in the sequence} \\ 0 & \text{otherwise} \end{cases}$
C_i	Completion time of patient *i* by the ASP
Ω_d	Discharge completion time of patient *t*
$\Omega'_{d'}$	Sorted list of discharge completion times (sorted in nondecreasing order)
β_b	Boarding time of upstream bed request *b*
$y_{d'd}$	List sorting variable; $\begin{cases} 1 & \text{if } \Omega_d \text{ is used as } \Omega'_{d'} \\ 0 & \text{otherwise} \end{cases}$

Several MIP formulations for a single-machine sequencing problem exist; see Keha et al. (2009). We chose a linear ordering variable formulation for this problem based on its performance as demonstrated by Keha et al. (2009) and on the fact that we did not want to over-specify the final sequence for an ASP by using a time-indexed formulation. A simple ordering of patients would be more intuitive to an ASP and easier to implement.

Our objective is to minimize total upstream boarding time:

$$\min BT = \sum_{b \in B} \beta_b \tag{1}$$

subject to:

$$C_i = t_0 + \sum_{\substack{j \in N \\ j \neq i}} p_j x_{ji} + p_i \quad \forall i \in N \tag{2}$$

$$\Omega_d = \max\{p_d + \rho_d, C_d\} \quad \forall d \in D \tag{3}$$

$$C_i \leq u_i \quad \forall i \in N \tag{4}$$

$$\Omega_d \leq \delta_d \quad \forall d \in D \tag{5}$$

$$x_{ij} + x_{ji} = 1 \quad 1 \leq i < j \leq |N| \tag{6}$$

$$x_{ij} + x_{jk} + x_{ki} \leq 2 \quad i, j, k \in N \text{ and } i \neq j \neq k \tag{7}$$

$$x_{ij} \in \{0,1\} \quad \forall i, j \in N \tag{8}$$

Constraints (2), (4), and (6)-(8) are standard single machine sequencing constraints for a linear ordering variable formulation, while Constraints (3) and (5) govern the additional processes required for a discharge patient. Constraint (2) defines the completion time of each patient by the ASP. Constraint (3) defines the discharge completion time for a patient in the discharge group. Constraint (4) enforces due dates for the patients to be seen by the ASP. Constraint (5) enforces discharge cutoff times (discharge completion due dates) for Group D patients. Constraint (6) is the set of conflict constraints, ensuring that either patient *i* is processed before patient *j* or patient *j* is processed before patient *i*; it also ensures that every patient is sequenced. Constraint (7) is the set of transitivity constraints, ensuring a linear order between three patients in the sequence. Constraint (8) is the set of binary decision constraints on the linear ordering variables.

The following constraints capture the system-wide impact of the proposed inpatient discharge planning model:

$$\beta_b = \max\{\Omega'_{d'} - \alpha_b, 0 \mid d' = u\} \quad \forall b \in B, \forall d' \in D \tag{9}$$

$$\Omega'_{d'} = \sum_{d \in D} \Omega_d * y_{d'd} \quad \forall d' \in D \tag{10}$$

$$\Omega'_{d'} \geq \Omega'_{d'-1} \quad d' = 2, \ldots, D \tag{11}$$

$$\sum_{d \in D} y_{d'd} = 1 \quad \forall d' \in D \tag{12}$$

$$\sum_{d' \in D} y_{d'd} = 1 \quad \forall d \in D \tag{13}$$

$$y_{d'd} \in \{0,1\} \quad \forall d', d \in D \tag{14}$$

Constraints (9)-(14) govern the assignment of upstream bed requests to beds emptied by discharge-ready patients. Constraint (9) defines the boarding time for each upstream bed request, assuming a FIFO assignment of requests to inpatient beds. For this constraint to correctly calculate the boarding time, a sorted list of discharge completion times (sorted in nondecreasing order) is required. Constraints (10)-(14) define this sorted list of discharge completion times.

Notice the nonlinear constraints (3), (9), and (10). While (3) and (9) can be easily linearized using standard techniques, we introduce a new decision variable, $z_{d'd}$, and replace the quadratic Constraint (10) with Constraint (10′). To achieve equivalence, we further add Constraints (15) and (16). Note that in Constraint (15), we introduce *M* as the upper limit of the discharge completion times; in our problem, this is 24, since all discharges must be completed by the end of the day.

$$\Omega'_{d'} = \sum_{d \in D} z_{d'd} \qquad \forall d' \in D \tag{10'}$$

$$z_{d'd} \geq \Omega_d - M(1 - y_{d'd}) \qquad \forall d', d \in D \tag{15}$$

$$z_{d'd} \geq 0 \qquad \forall d', d \in D \tag{16}$$

5.4 Solution Approach and Strategy Derivation

5.4.1 Practical Considerations in Solving the Stochastic ASP Sequencing Problem

While a sophisticated stochastic programming algorithm could be developed to solve the underlying sequencing optimization problem under uncertainty, this would likely not be used in practice due to constraints on the solution time (e.g., a provider would prefer solutions in a matter of seconds) and integration with hospital legacy systems. In addition, our experience working with the hospital units suggests that care providers prefer solutions that are easy to understand and remember, and are consistent from day to day. Thus, deriving a single decision rule from an optimization model that is easy to understand and promising to all the scenarios results in a higher likelihood of implementation. In some sense, we can refer to such schedules as robust to deviations from all possible scenarios (i.e., realizations of the uncertainties). We, therefore, propose a meta-heuristic approach to solve this problem that uses the fact that the scenario-specific deterministic model can be solved quickly using a commercial solver (e.g., CPLEX v12.7).

We first refer to the system configuration via four attributes that define the ASP's workload on a given day: (i) the total number of patients; (ii) the percent of patients in each of the three patient groups (D, A, R); (iii) the percent of patients in Groups A and R with due dates; and (iv) the percent of patients in Group D with discharge cutoffs. Each of these would usually be known by the ASP at the start of the shift with a fair amount of certainty. For a specific system configuration, we generate a large set S of scenarios which are potential realizations of the stochastic variables (i.e., ASP processing times, discharge processing times, and bed request arrival times). For each scenario $s \in S$, we solve the MIP model optimally using CPLEX, which provides an optimal sequence for that specific scenario. These scenario-specific optimal sequences are in terms of jobs, e.g., {4,2,5,8,3,10,1,6,7,9}, which can be translated more meaningfully to the ASP as {A,D,A,R,D,R,D,A,R,R}, where Group D = jobs 1-3, Group A = jobs 4-6, and Group R = jobs 7-10.

It is quite possible that each scenario may result in a different sequence of patients than the others for the same system configuration. We, therefore, develop an approach to analyze all of the scenario-specific optimal sequences for a given configuration in order to derive a single strategy that addresses the system constraints and clinician preferences. This derived strategy will also be able to further guide the ASP on the following: which specific patients in the D, A, and R groups should be sequenced in the positions assigned to their group? Which group positions should be given to patients with due dates? Should the patients be sorted within their groups, and if so, how?

5.4.2 Strategy Derivation

We propose a Simulated Annealing (SA) algorithm to derive a single strategy for a given configuration such that it is promising to all the scenario-specific MIPs. SA is a proven approach for such a combinatorial problem (Lin et al., 2009; Loukil et al., 2007;

Eglese, 1990). SA improves upon an existing feasible sequence by swapping jobs across positions. To measure the performance of any strategy, we consider its difference on the boarding time from the optimal strategy derived for each specific scenario. We then define our primary performance metric to be the average of the differences over all the scenarios. In summary, we seek to minimize the average resultant deviation from the scenario-specific optimal boarding time, i.e.,

$$\min \frac{1}{|S|} \sum_{s \in S} |BT_s^{SA} - BT_s^{MIP}| \,, \tag{17}$$

where BT_s^{SA} is the boarding time resulting from the application of the single SA-derived strategy in scenario *s* and BT_s^{MIP} is the optimal boarding time found via solving the MIP specific to scenario *s*.

To ensure the ease of implementation of our strategy, we consider three decision points in the proposed SA and construct the solution accordingly: (i) which patient group to assign to which position; (ii) within each patient group, where to assign the patients with due dates (or discharge cutoffs if a discharge); and (iii) how to sort the patients within each group by expected processing time (or total discharge processing time, comprising the ASP processing time plus the remaining unit discharge processing, for discharges).

An illustration of our solution representation is demonstrated in the following potential strategy: {R_1, A_1, R_1, D_1, D_2, D_1, A_2, R_2, A_2, R_2, 1,1,3,2,3,1}. The first ten spots in the solution representation correspond to *positions* in the sequence. Each position is assigned to one of the three patient groups, D, A, or R, further subdivided into patients with due dates or discharge cutoffs, denoted by the subscript 1, and those without due dates or cutoffs, denoted by the subscript 2. Essentially, there are six subgroups of patients which may be assigned to the positions in the sequence. The initial solution has the correct number of positions allocated to each subgroup for the system configuration in question. The SA algorithm is then employed to decide which positions to assign to which subgroup by swapping patients between positions.

The last six spots in the solution representation correspond to *sorting* for each of the six patient subgroups described previously. When the chosen strategy is applied, the patients within each group must be sorted in some order. We introduce six flags at the end of the solution representation, each of which is for the D_1, D_2, A_1, A_2, R_1, and R_2 subgroups, respectively. The first two flags can take on a value between 1 and 5, dictating a sorting operation by the shortest expected total discharge processing time, longest expected total discharge processing time, shortest expected ASP processing time, longest expected ASP processing time, or randomly (no sorting), respectively. The last four flags can take on values between 1 and 3, dictating a sorting operation by the shortest expected ASP processing time, longest expected ASP processing time, or randomly (no sorting), respectively.

A neighborhood is then defined as a combination of two decisions, a positional swap and the sorting choice. The neighborhood of the positional portion of the solution representation is defined as a random swap between two patients in different subgroups. We only consider swapping between patients in different subgroups and not patients within the same subgroup (thus, a D_1 can be swapped with any D_2 but not with another D_1). The within-subgroup ordering of patients is accounted for by the sorting technique applied to each subgroup. The neighborhood of the sorting portion of the solution representation is defined as a random choice of a value for each of the six sorting variables.

Once a potential solution in the neighborhood of the current solution has been generated, it is then evaluated and compared to the current solution in terms of the average deviation as shown in Equation (17). However, there is no guarantee that a potential strategy will always maintain feasibility in terms of meeting due dates and discharge cutoffs (e.g., subgroups D_1, A_1, and R_1). Thus, we calculate post-hoc, for a strategy, two additional performance criteria across all scenarios: the average numbers of violations of (i) due dates and (ii) discharge cutoffs. If the strategy results in any infeasibilities (i.e., violates the constraints in some scenario-specific instances) based on these two criteria, it is rejected; if it is feasible, then it is accepted (i) always if it is strictly better than the current strategy, (ii) with 50% probability if it is equal to the current strategy, or (iii) based on the standard SA acceptance probability (based on the Boltzmann distribution) if it is worse (Eglese, 1990).

The initial temperature chosen for our SA was 1.0, with a constant proportional decrease rate of 0.9. The stopping criterion for the SA was two-fold: (i) minimum temperature or (ii) number of non-improving moves. We modified our SA to save all the equally best solutions it found. Our SA was coded in Python v3.5.

5.5 Experimental Evaluation of Our Approach

5.5.1 Experimental Framework and Data

For our experimental evaluation, we focused on the ancillary service responsible for care management in the inpatient setting given their logistical role in executing discharges. However, our approach is generic for ancillary services responsible for other tasks in an inpatient setting. To this extent, we collected 1,303 de-identified patient records for 2015 from one of the IUs at a large teaching hospital in the Northeast US. We also interviewed 10 RN and SW care managers across 5 IUs (renal, neurology, oncology, cardiovascular, and advanced inpatient medicine) at this hospital. See Section 5.7 for a summary of these interviews. Based on the responses from our interviews, we derived the factor levels as indicated in Table 5-4. The combinations of these factors and levels result in a total of 24 different configurations.

Table 5-4: Design Framework for System Configurations

Factor	Description	Levels	Level Details
N	Number of patients	L H	Low (10) High (20)
DAR	Percent of patients in the three groups	B DH DL	Balanced (30%, 30%, 40%) Discharge heavy (50%, 20%, 30%) Discharge Light (10%, 40%, 50%)
DD	Percent of patients in groups A and R with due dates	MH ML	Morning Heavy (40%) Morning Light (20%)
DC	Percent of patients in group D with discharge cutoffs	NHH NHL	Non-Home Heavy (60%) Non-Home Light (15%)

In Table 5-4, we consider two levels of the number of patients (N), i.e., 10 (L) and 20 (H), to be seen by the ASP on a given day. These may represent two different providers on the same unit (SWs typically have fewer patients than RNs due to the complexity of their cases), or ASPs from the same service on different IUs, or two different days for the same provider on the same unit. The second factor (DAR) controls the distribution of the patients across the three patient groups D, A, and R. The first level, B (where D=A=30% and R=40% of the patients), suggests a reasonably similar number of patients in each group; DH and DL consider situations when there are more and fewer discharge patients, respectively. The third factor (DD) controls the percent of Group A and R patients with due dates of 12 noon (the rest have no due dates), representing the real challenge faced by care managers that may need to see the patients in the morning, competing with their usual focus on discharges first. We consider 40% (MH) of both A and R patients to be seen by noon as a particularly busy morning; 20% (ML) would be a lighter morning. The last factor represents the percent of Group D patients with a discharge cutoff of 3 p.m., based on the typical time when a patient being discharged to a facility (long-term care, nursing home, etc.) would need to leave the hospital in order to ensure transportation and admission to the downstream facility; 60% (NHH) suggests a day or a unit with a large proportion of these non-home discharges, while 15% (NHL) suggests a day or a unit with more home discharges.

For each one of the 24 system configurations, there are three stochastic elements specifying the scenarios: ASP processing time for each patient, discharge process time for the discharges, and bed request arrival times. For ease of comparison across scenarios for a given configuration, we estimated the expected bed request times, where B is the set of bed requests times, $|B| = |D|$ ensuring that the total number of bed requests is the same as the number of discharges. The arrival times were generated ahead of time according to the following algorithm:

(1) For a given system configuration (for which $|D|$ is known), draw $|B|$ random arrival times from a Normal 3-mixture distribution; this distribution best fit the 2015 dataset ($p<0.05$) with the lowest AIC value (see Section 5.8.1).

(2) Sort these times in nondecreasing order.

(3) Repeat steps (1) and (2) 1,000 times.

(4) Find the average arrival time for each of the $|B|$ positions across the 1,000 replications.

Table 5-5 summarizes the expected bed request times derived from the above approach.

Table 5-5: Expected Bed Request Arrival Times of Day

N	DAR	$\lvert B \rvert$	Expected Arrival Times (24-hour notation)
L	B	3	(9.24, 13.65, 17.23)
L	DH	5	(7.33, 11.29, 13.67, 15.8, 18.5)
L	DL	1	(13.53)
H	B	6	(6.69, 10.72, 12.87, 14.46, 16.43, 19.04)
H	DH	10	(4.67, 8.57, 10.97, 12.27, 13.2, 14.09, 15.11, 16.35, 17.97, 20.1)
H	DL	2	(10.78, 16.09)

The remaining two stochastic elements, ASP processing times and discharge processing times, were generated for each scenario according to prespecified distributions. Data collected in interviews of ASPs for the ASP processing times were not enough to generate statistically significant curve fits; instead, the data provided likely averages and upper and lower bounds for these times. For this reason, we assumed group- and configuration-specific Triangular(a,b,c) distributions, where a, b, and c were derived from these interviews. For the discharge process times (in hours), we used a Triangular(8, 13.99, 20) distribution from the 2015 dataset. See Section 5.8.2 and Section 5.8.3 for further details.

We generated 1,000 scenarios for each of the 24 system configurations. When generating these scenarios, we ensured that the total ASP time required across all patients (sum of the processing times) was within 7.5 hours (excluding morning rounds/huddle and other administrative tasks from a typical 9-hr workday). Solving the scenario-specific MIP model in each of these 24,000 scenarios required approximately 1.5 hours.

5.5.2 SA Solutions

We first evaluated the performance of the SA-derived strategy for each of the 24 configurations. Although the objective of the SA was to minimize the average deviation of boarding time (in hours) for each scenario from the optimal solution of the scenario-specific MIP model, we used additional statistics such as standard deviation, median, and interquartile range (IQR). Table 5-6 summarizes these quantities across the 24 configurations. As an example, Figure 5-4 illustrates the distribution of the sample deviations across 1,000 scenarios for a specific configuration #5 (i.e., L/B/MH/NHH). The algorithm took roughly 20-30 minutes to solve the smaller patient cases, and 1-3 hours for most of the larger cases. The larger DH cases, being the most constrained, took the longest to converge, between 3.5 and 6.8 hours.

Table 5-6: Robustness of the SA Strategies across All Scenarios (Hrs)

	Configuration	Mean	Std. Dev.	Median	IQR
1	L/DH/MH/NHH	0.36	0.61	0.00	0.56
2	L/DH/MH/NHL	0.25	0.47	0.00	0.31
3	L/DH/ML/NHH	0.22	0.49	0.00	0.19
4	L/DH/ML/NHL	0.13	0.32	0.00	0.00
5	L/B/MH/NHH	0.44	0.62	0.07	0.72
6	L/B/MH/NHL	0.23	0.46	0.00	0.20
7	L/B/ML/NHH	0.20	0.42	0.00	0.14
8	L/B/ML/NHL	0.00	0.00	0.00	0.00
9	L/DL/MH/NHH	0.00	0.00	0.00	0.00
10	L/DL/MH/NHL	0.00	0.00	0.00	0.00
11	L/DL/ML/NHH	0.00	0.00	0.00	0.00
12	L/DL/ML/NHL	0.00	0.00	0.00	0.00
13	H/DH/MH/NHH	0.26	0.50	0.00	0.30
14	H/DH/MH/NHL	0.11	0.30	0.00	0.00
15	H/DH/ML/NHH	0.08	0.26	0.00	0.00
16	H/DH/ML/NHL	0.05	0.19	0.00	0.00
17	H/B/MH/NHH	0.15	0.32	0.00	0.09
18	H/B/MH/NHL	0.20	0.40	0.00	0.20
19	H/B/ML/NHH	0.04	0.14	0.00	0.00
20	H/B/ML/NHL	0.03	0.13	0.00	0.00
21	H/DL/MH/NHH	0.27	0.43	0.00	0.52
22	H/DL/MH/NHL	0.15	0.30	0.00	0.04
23	H/DL/ML/NHH	0.04	0.15	0.00	0.00
24	H/DL/ML/NHL	0.00	0.00	0.00	0.00

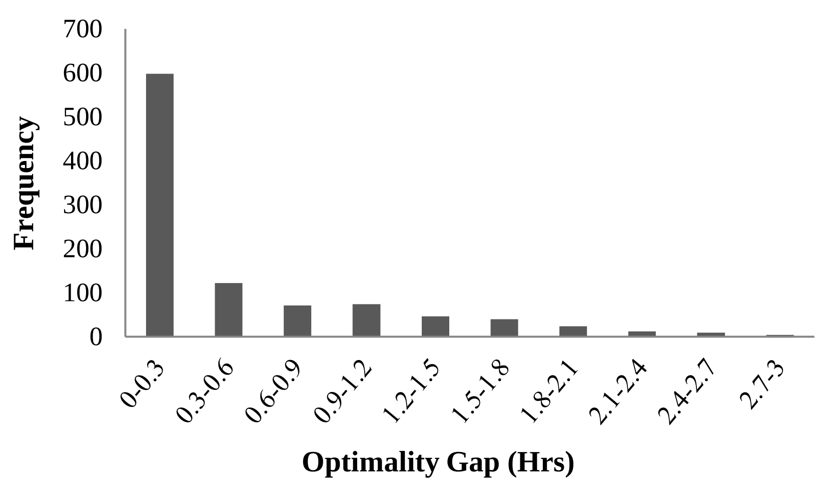


Figure 5-4: Distribution of Sample Deviation from Optimal for Configuration 5

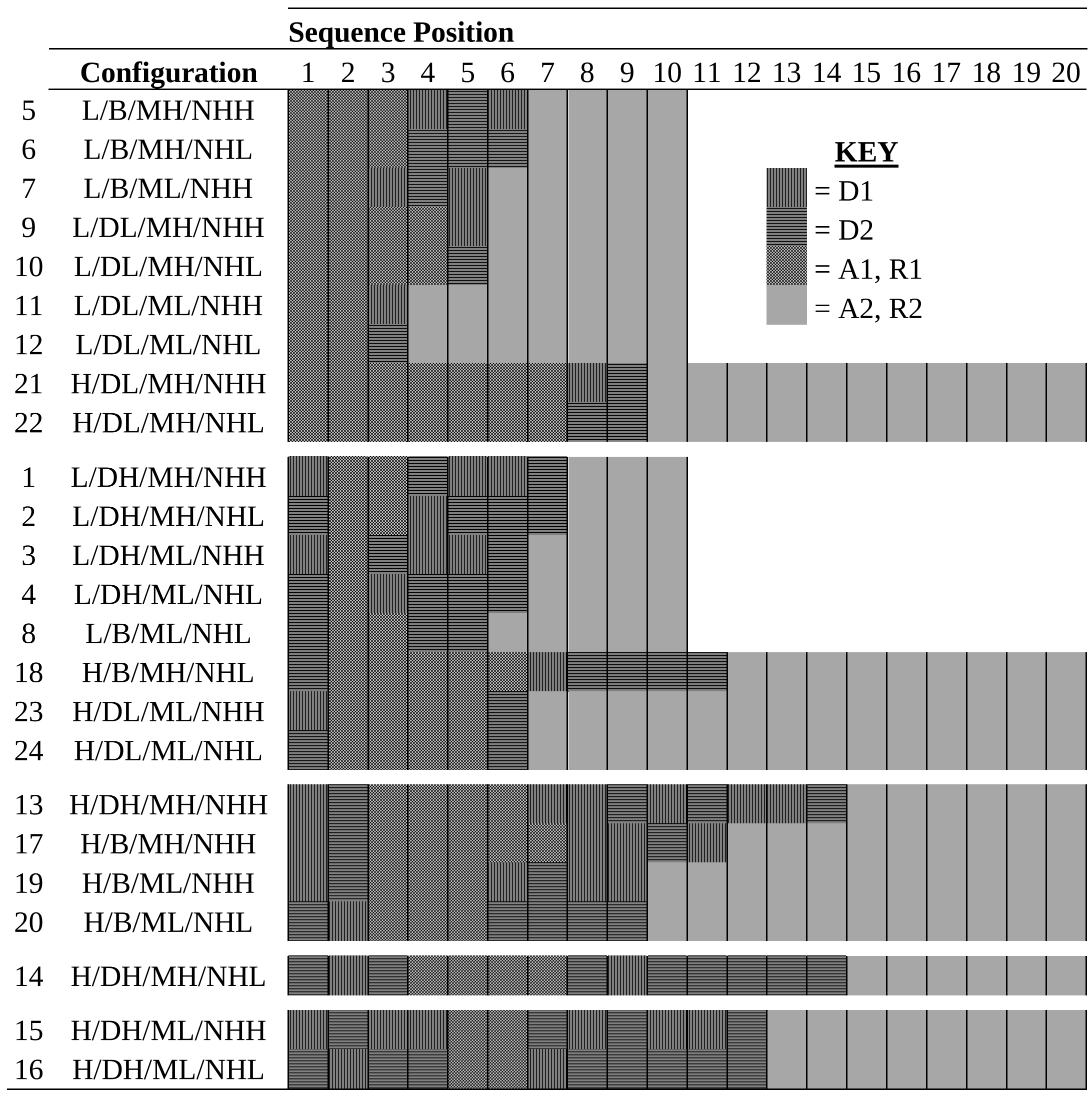
Notice in Table 5-6 that the mean deviation across all the configurations was 0.13 hrs (7.8 minutes). The corresponding medians were 0 minutes, which suggests that the derived strategies frequently achieved optimal boarding time. Figure 5-4 illustrates that even in the case with the worst deviation from optimal (Configuration #5), the SA-derived strategy for this configuration resulted in less than 18-minute deviation from optimal in 60% of the scenarios. The reason that in a few scenarios the SA-derived strategies performed worse was likely due to the unique features inherent in those scenarios. Naturally, such occurrences were more frequent in more constrained cases, such as DH, MH, and MHH. These findings led us to believe that the SA-derived strategies were of good quality. With this evidence, we further analyzed the structure of the SA-derived strategies across all configurations to see if they could be grouped into broader categories.

For many configurations, SA found several alternate best solutions (with the same objective value). This was because of multiple orderings within the A_1, R_1, A_2, and R_2 subgroups. That is, while the discharge patients, D_1 and D_2, were usually tightly constrained to specific positions, the A_1 and R_1 patients were usually grouped together in early positions in any order, and the A_2 and R_2 patients were almost always grouped together in the last positions in any order. For example, for Configuration 5, {R_1, A_1, R_1, D_1, D_2, D_1, A_2, R_2, A_2, R_2}, {R_1, R_1, A_1, D_1, D_2, D_1, R_2, A_2, R_2, A_2 }, and { A_1, R_1, R_1, D_1, D_2, D_1, A_2, R_2, R_2, A_2} all resulted in equally best solutions.

Further, across all configurations, if there were more than one patient in the D_1 or D_2 subgroup, that subgroup was sorted by the shortest expected total discharge processing time. We did not notice any sorting in the A and R subgroups.

The above observations allowed for the 24 strategies, one each for the 24 configurations, to be further aggregated into 5 groups, as illustrated in Table 5-7.

Table 5-7: Strategies from Simulated Annealing



Notice the priority shift of patients in D_1 and D_2 subgroups towards the front of the sequence as the number of discharges increased across configurations (either as a factor of the number of patients or as a factor of the percentage of discharges). In general, this correlates with the problem complexity. With more patients, there are more possibilities for sequencing. With more discharges relative to the other groups, there are more possibilities to prioritize discharges without violating due date constraints for A and R patients. Intuitively, prioritizing more discharges earlier in the sequence, when possible, is preferred in order to minimize the boarding time of upstream patients. However, the ordering within discharges of D_1 and D_2 subgroups was specific to the different configurations. That is, while the positioning of discharges relative to A and R patients followed similar patterns in the 5 broader groups, the discharge positions allocated to D_1 and D_2 patients specifically were dependent on the number of discharges and whether that configuration was NHH or NHL.

5.5.3 Strategy Comparisons

While SA was able to find high-quality strategies for all 24 configurations, and these high-quality strategies could be grouped into 5 overarching SA-derived strategies, we wanted to compare them with single strategies that could be applied across allthe 24 configurations. Such single strategies may be even easier to understand, remember, and implement from day to day in practice. We, therefore, considered 6 other strategies for comparison with the 5 SA-derived strategies, as listed in Table 5-8.

Table 5-8: Alternate Strategies

Strategy	Details
P_1	A and R patients with due dates first, then discharges with cutoffs, then the rest of discharges, then the rest of A and R patients; within each discharge subgroup, sort by the shortest expected total discharge processing time
P_2	A and R patients with due dates first, then discharges, sorted by the shortest expected total discharge processing time (regardless of cutoffs or not), then the rest of A and R patients
P_3	Discharges with cutoffs first, then discharges without cutoffs, then newly arrived patients with due dates, then newly arrived patients without due dates, then recurring patients with due dates, then recurring patients without due dates
P_4	One discharge first (non-home if non-home-heavy day, home if not), then A and R patients with due dates, then discharges with cutoffs, then the rest of discharges, then the rest of A and R patients; within each discharge subgroup, sort by the shortest total expected discharge processing time
P_5	"Earliest Due Date"; A and R patients first (12 noon due date), then non-home discharges (15 p.m. discharge cutoff), then rest of patients in any order
P_6	"Shortest Processing Time"; sort all patients, regardless of subgroup, by the shortest expected ASP processing time

The first two strategies were derived from our knowledge of the problem and observation of the patterns that emerged across the SA sequences. We aggregated the SA strategies into two simpler ones, P_1 and P_2. Both these strategies placed A_1 and R_1 patients in the first spots in the sequence in any order, followed by discharges, followed by the A_2 and R_2 patients in any order. However, in P_1, all D_1 patients were placed before the D_2 patients; each discharge subgroup was sorted by the shortest expected total discharge processing time. In P_2 discharges were simply sorted according to the shortest expected total discharge processing time. None of the other groups were sorted by any pattern.

The third strategy, P_3, was derived from our interviews with the ASPs, who often preferred to focus on discharges first, then newly arrived patients, then recurring patients. Patients within each group were sorted only by due dates or discharge cutoffs. The fourth strategy, P_4, was proposed in a different study (Parikh et al., 2017; Ballester et al., 2017). The last two strategies, P_5 and P_6, were adaptations of proven sequencing rules from the deterministic machine sequencing literature (i.e., earliest due date, EDD, and shortest processing time, SPT); we wanted to examine their generalizability to our problem.

The 6 alternate strategies and the 5 SA grouped-strategies (collectively referred to as P_{SA}) were compared across their corresponding average deviations from the optimal boarding time (see Figure 5-5).

For P_1, because A_1 and R_1 patients were always placed before any D patients, the boarding time gap was much worse than P_{SA}'s gap in problem instances where P_{SA} sequenced some discharges before A_1 and R_1 (all but 9 configurations). Additionally, because P_1 always placed D_1 before D_2 patients, it performed worse than P_{SA} in configurations with higher percentages of non-home patients. In such configurations, P_{SA} could intersperse the positions of the two groups and thereby place more of the expected shorter discharges earlier while still being constrained by the discharge subgroups. However, P_1's prioritization of A_1 and R_1 before D_1 before all other patients allowed it to always maintain feasibility in both due dates and cutoffs.

P_2 relaxed the second limitation of P_1 (always prioritizing D_1 before D_2) and simply sorted discharges by the shortest expected total discharge processing time, ignoring the discharge subgroups entirely. Thus, it performed much better than P_1, and in small problem instances (Configurations 1-12) it typically outperformed P_{SA}, since P_{SA} was still limited by the assignment of discharge subgroups to specific positions. However, this aspect of P_2 led to discharge cutoff violations in 9 configurations, since there is no guarantee that D_1 patients will meet their cutoffs in P_2. Additionally, because

P_2 still placed all A_1 and R_1 patients before any discharges like P_1, it performed worse than P_{SA} in most large problem instances (Configurations 13-24). Like P_1, this prioritization did guarantee that P_2 did not violate due dates.

Despite the fact that P_3 placed all discharges first, it consistently performed poorly. This is due to the fact that this strategy did not sort discharges at all, illustrating the necessity of some sorting mechanism for discharges. Nonetheless, in situations with lower numbers of discharges, it performed close to or better than P_{SA}, as the sorting is not as critical when there are only 1 or 2 discharges. This focus on discharges first naturally ensured that P_3 did not violate cutoffs. Conversely, this resulted in P_3 having the most due date violations; it always missed some due dates for the other patients.

P_4 was structurally similar to P_1, with the only difference being that it always placed one discharge before the A_1 and R_1 patients. This allowed it to outperform P_1 in all configurations. However, like P_1, it was still limited to placing all D_1 before D_2 patients when processing discharges after the A_1 and R_1 patients. While this guaranteed that it did not violate discharge cutoffs, it prevented P_4 from outperforming P_{SA} in cases with larger numbers of discharges. However, in configurations with smaller numbers of discharges P_4 performed very close to P_{SA}, and in several of these cases it outperformed P_{SA}. These were typically configurations when P_{SA} did not place any discharges before the A_1 and R_1 patients in order to maintain due date constraints. In all 9 configurations where P_{SA} did not sequence any discharges first, P_4 violated due dates. This further illustrates the tradeoff between prioritizing discharges and meeting due dates for A and R patients.

The machine sequencing rules, P_5 and P_6, performed the worst on the boarding time measure across all configurations. For P_5, this was because: discharges were not placed before A_1 and R_1 patients, all D_1 were placed before D_2 patients, and discharges were not sorted. P_6 represents a myopic view of the ASP when sorting the patients based solely on the ASP's processing time with each, which leads to poor performance. P_5 did not violate due dates or discharge cutoffs (i.e., this is the nature of EDD), while P_6 violated both due dates and discharge cutoffs. Thus, for ease of display we do not include them in Figure 5-5.

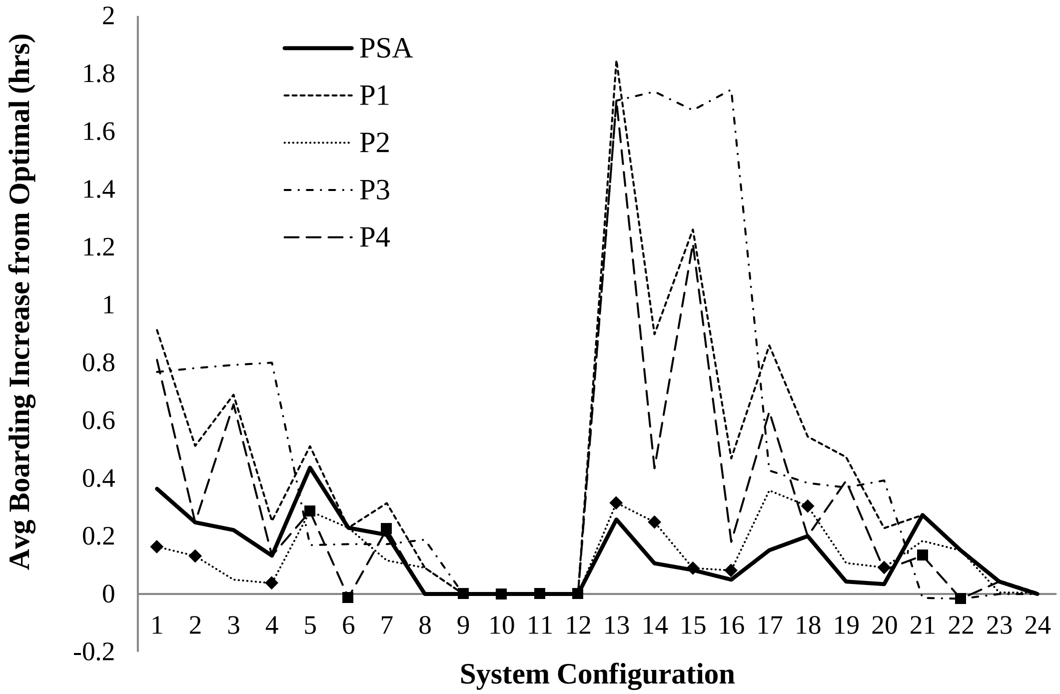


Figure 5-5: Strategy Comparison on Average Boarding Time Increase from Optimal

◆ = configuration with discharge cutoff violations for P_2

■ = configuration with due date violations for P_4

Figure 5-5 shows that P_{SA} performed much better than all other strategies on the average deviation in boarding time, while meeting due dates and discharge cutoffs. Similarly, P_1, which was also constrained by discharge subgroups, did not violate due dates and cutoffs, but failed to outperform P_{SA} in boarding time because of the placement of D_1 patients before D_2 patients; in P_{SA} these positions can be interchanged. Since P_2 was not constrained by discharge subgroups, it outperformed P_{SA} in boarding time in small problem instances (i.e., Configurations 1-12) and it did not violate due dates. However, it could not guarantee feasibility in meeting discharge cutoffs. Additionally, due to the fact that A_1 and R_1 patients were always placed before any discharges, P_2 performed worse than P_{SA} in large problem instances (i.e., Configurations 13-24). P_3 occasionally outperformed P_{SA} due to its focus on discharges first, but in general P_3 failed to perform well because D_1 patients were always placed before D_2 patients and neither discharge subgroup was sorted. The discharge-focused nature of P_3 caused it to consistently violate due dates, although it did not violate discharge cutoffs. By placing one discharge first, P_4 outperformed P_1 and sometimes P_{SA}, but at the cost of due date violations. P_5 and P_6 had the worst boarding time gaps. P_5 consistently maintained feasibility. P_6 rarely maintained feasibility in due dates or discharge cutoffs. Table 5-9 summarizes the performance of these strategies across all 24 configurations.

Table 5-9: Strategy Comparison (Summary across All 24 Configurations)

Strategy	Mean Deviation from Optimal (Hrs)	Mean # Due Date Violations	Mean # Cutoff Violations
P_{SA}	0.134	0	0
P_1	0.440	0	0
P_2	0.127	0	0.017
P_3	0.510	2.522	0
P_4	0.306	0.125	0
P_5	1.655	0	0
P_6	3.054	0.765	0.494

Note that one of these strategies (i.e., P_2) may appear to perform better than the SA-derived strategies, but at the cost of occasional violations in discharge cutoffs.

Although occasional, their impact could be quite severe; e.g., missing a discharge cutoff by a few minutes could result in missing the last shuttle to a long term care facility, causing an unnecessary overnight stay at the unit. P_4 was the next closest contender to P_{SA}, but resulted in over double the mean deviation of P_{SA} and occasionally violated due dates. Nonetheless, this might be more acceptable than P_2 to an ASP who desires a single strategy for any situation and with the latitude to prioritize discharges at some tolerable expense to other patients. P_1, at triple the mean deviation of P_{SA}, was the next best strategy that was always feasible.

5.6 Conclusions

In this work, we examined a real problem faced by ancillary service healthcare providers (ASPs) serving an inpatient unit. An ASP plays an important logistical role in discharge planning. As a limited resource on inpatient units, ASPs can significantly affect the flow of patients on the unit and the hospital overall. However, the ASP must balance a focus on discharges with the needs of the other patients that must be seen every day. This necessitates efficient sequencing of the ASP's patient workload. In order to be useful, such a sequence would need to be simple enough to understand, remember, and implement every day but also robust to the daily variability in healthcare.

To address this problem, we proposed a framework that combined mathematical modeling, scenario sampling, and meta-heuristics to derive implementable strategies. Real data and interviews with ASPs at a large teaching hospital led to the derivation of 5 strategies, specific to a set of configurations. These strategies not only resulted in the least deviation from optimal boarding time but also avoided violating any constraints. Single-strategy approaches may perform almost as well as SA-derived strategies, but they may occasionally violate due dates or cutoffs, with varying degrees of implications, e.g., violating the hospital 24-hour window of seeing a newly-arrived patient, delaying the activities of other providers for a recurring patient, or potential overnight stays if a cutoff is missed for a discharge-ready patient. Thus, such strategies trade feasibility for ease-of-implementation.

Broader insights we derived in this study suggest: (i) having a focus on newly-arrived and recurring patients with due dates first, then discharges, then the rest of the patients; (ii) increasing prioritization of discharges over patients with due dates as the proportion of discharges and/or the total number of patients increases; and (iii) ASPs maintaining a systemic prioritization of discharges by total expected discharge processing time, rather than a myopic prioritization based only on the ASP's workload.

Future work in this area could focus on relaxing some of the modeling assumptions and assessing the potential generalizability of our approach. For instance, our model could be extended to account for blocking of the ASP by other services, unexpected new patients/interruptions, and/or ASP compliance rate to the suggested sequence. Evaluating our approach using data from a different unit or hospital will evaluate generalizability and applicability of our findings across inpatient units.

5.7 Appendix A: Summary of Care Manager Interviews

Table 5-10: Interview Characteristics and System Estimates

Interview #	Unit/Service	Care Manager Category	Unit Size (Beds)	Patients per day (range)		Discharges per day (range)		New evals per day (range)	
1	Renal	RN	35	14	18	4	7,9	4	7,9
2	Neuro	SW	24-9	10	15	2	5,6	2	5,6
3	Oncology	SW	40	8		1	2	1	
4	AIM	RN	29	13	18	2	8	4	5
5	Oncology	RN	40	15	20	1	5	5	6
6	AIM	SW	29	8	10	3	4	2	4
7	Neuro	RN	24-9	18		1	7	1	7
8	Renal	SW	35	10	12	2	3	3	4
9	Cardio	RN	40	24		4	5	4	5
10	Cardio	SW	40	13		1	2	2	3

Table 5-11: ASP Process Time Estimates

	Processing Time Estimates (in minutes unless otherwise noted)								
Interview #	Discharges			New Evals			Recurring		
1									
2	15	20	2 hrs	15	20	30-45		35-40	1 hr
3	30	2 hr	3 hr	30	45	60	20	30	60
4	30	1.5 hrs	2 hrs	10	15-20	30	10	25	60
5	20	45	2 hrs	15	30	60	10	30	45
6	0.5 hrs	1.5	2.5	20	30	45	15	20-30	60
7	10	30-45	60	5	15	45-60	10	20	30
8	30	1 hr	2-3 hrs	30	30	50	10	30	1 hr
9	45-60		2 hrs		1 hr		15-20	30	45
10	15	1 hr	2 hrs	30	45	60	15	1 hr	2.5 hrs

Table 5-12: ASP Process Time Distribution Estimates

	Processing Time Percentage Estimates (distribution across min, mid, max)								
Interview #	Discharges			New Evals			Recurring		
1						10%			25%
2	30%	30%	40%			10-15%			2-3/day
3	2/day		1/week	15%	15%	70%	10%	50%	40%
4	25%	50%	25%	20%	60%	20%	50%	25%	25%
5	50%		3/week		60%	3/week	25%	50%	25%
6	10%	60%	30%		60-70%		5-10%		5-10%
7						1/week			
8	25%	25%	50%						
9	30%		60%				30%		40%
10		25%	30%	40%	30%	<10%		35%	15

Table 5-13: Typical Patient Prioritization Followed

Interview #	Prioritization
1	Discharges--Evals--Recurring
2	Discharges--Pressing Problems--Evals--Everyone Else
3	Discharges--Social Needs (20% Recurring)--Evals--Rest of Recurring
4	Discharges--75% Evals--Recurring--Rest Evals
5	Discharges--Observations (5% Recurring)--Evals--Rest of Recurring
6	Actively dying (5% of time)--Discharges--Evals--Recurring
7	Discharges--Evals--Recurring
8	Discharges (Rehab before home)--Evals--Recurring
9	Discharges--Evals--Recurring (Home Health first)
10	Discharges--Evals--Rest

Table 5-14: Typical Due Dates and Cutoffs

Interview #	Discharge Cutoffs	New Evals Policy	Due Dates
1	Not very frequent	Try to see same day	Dialysis patients--can only see before or after dialysis, but they can go for dialysis at any time
2	Shuttle runs till 9; some facilities have cutoffs but not many	Within 24 hrs of patient arrival	
3	Discharge prep wrapped up by 4 pm; 6 pm pretty late to leave	Within 24 hrs	
4	Don't really find cutoffs for facilities; some rural facilities have 3 pm, 4 pm cutoffs (5-10%); tertiary care, so sometimes discharge 2-3 hrs away, can't have patient leave at 3-4 pm and not arrive at facility till 6 or 7 pm, usually work with facility to make happen next day at 10 am	Within 24 hrs	
5	Typically before 6 pm	Within 24 hrs	
6	Facilities need all paperwork, authorizations by 3 pm (70% of time)--elder care, lot of dementia patients	Within 24 hrs	
7	To facilities not after 3 pm or 5 pm--60-40 non-home to home ratio	Within 24 hrs	
8	Some facilities set limits; 4 pm standard (standalone, smaller facilities --40%; larger facilities will work with unit, but still want patients by 5 pm)	Within 24 hrs	
9	Try by 3 pm (11 am - 1 pm)	Within 24 hrs	
10	Rehab discharges should be by 4 pm	Within 24 hrs	

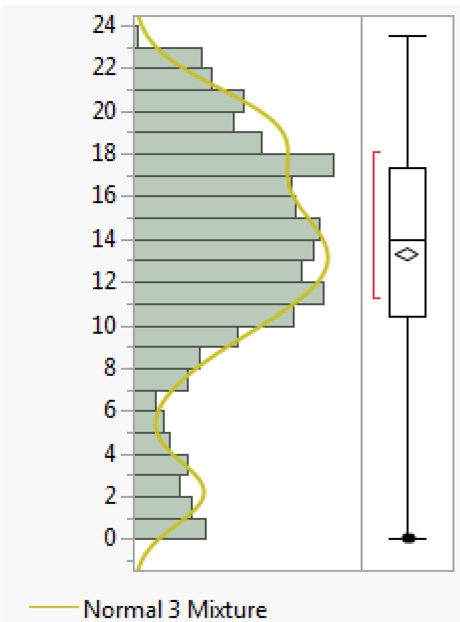
Table 5-15: Start of Day and Other Notes

Interview #	Start of Day	Other Notes
1	Ancillary dept rounds every day	Another group of patients: new to me but transfer from another unit so d/c plan made and ready to go already
2		
3		
4	9 am start (7:15 come in, organize; 8 am nursing huddle)	Some initial assessments/discharges same day (people came in over weekend)
5	Break in morning for 10 am rounds	Specialty unit; lot of variability across patients
6	7:30 am review charts; rounds 8:30-9; come back and divvy up patients with RN	Following 13-15 patients per day--don't see all on daily basis
7	Sit in nursing huddle at 8 am	
8	Chart review for 30 mins, then rounds for 30-45 mins	15 patients on caseload--don't see all on daily basis. Long stay patients--complex socially; nurse CMs don't see often; different relationship with these patients. Note should be written on patient at least every 5 days. 2 pm is high discharge time due to physician patterns. About 5 hrs per day total across more complex patients (50% of patients).
9	No rounds or nursing huddle on floor; go through list in morning with other RN and SW CM on floor	Sometimes overlap and cover other units if someone calls in sick. On weekends, cover 4 floors; prioritize discharges (not time for other patients).
10		Patients on 3 units: 2 on same floor (CICU and R9), one on another (R7); go back and forth between units; nowhere to work on R9/CICU, so R7 is home base. Not many discharges (more complex patients, so longer stays); if any, usually from R9 or R7. New evals usuallly in CICU or R7. CICU patients very sick, so wait for family to be around before going to see; sick and will be here a while, so don't think appropriate to bother them right away. Will put note in, but may not see patient right away.

5.8 Appendix B: Data Generation Methodology

5.8.1 Data for Bed Request Times

Based on the retrospective 2015 dataset from the inpatient unit, bed request arrival times can be modeled according to the following Normal 3 mixture distribution: Normal(2.212, 1.506) with probability 0.11; Normal(13.096, 3.369) with probability 0.67, Normal(19.333, 1.989) with probability 0.22. The statistics of the bed requests are displayed in Figure 5-6.



Quantiles

100.0%	maximum	23.55
99.5%		22.7992
97.5%		22.02
90.0%		20.126
75.0%	quartile	17.3
50.0%	median	13.95
25.0%	quartile	10.4
10.0%		4.274
2.5%		0.804
0.5%		0.05
0.0%	minimum	0

Summary Statistics

Mean	13.325418
Std Dev	5.4883749
Std Err Mean	0.1520448
Upper 95% Mean	13.623698
Lower 95% Mean	13.027139
N	1303

Figure 5-6: Statistics of the Bed Request Arrival Times at the Unit in 2015

5.8.2 Method of Generating ASP Process Times

Based on our interviews with the ASPs, we derived the relationships among the average processing times for the 3 patient groups as shown in Table 5-16.

Table 5-16: Summary of ASP Process Times from Care Management Interviews

Patient Group	Mean	Min	Max
D	---	0.4*$\overline{D}$	2*$\overline{D}$
A	0.5*$\overline{D}$	0.6*$\bar{A}$	1.5*$\bar{A}$
R	0.5*$\overline{D}$	0.4*$\bar{R}$	2*$\bar{R}$

In the model, we assume the ASP day length to be 7.5 hours (a 9-hour day minus 1 hour in the morning for nursing huddle and/or rounds, followed by 0.5-hour discussion with the other care manager on the unit to divide the patients appropriately between themselves).

We then have the following formula:

$$|D| * \overline{D} + |A| * \bar{A} + |R| * \bar{R} = 7.5$$

The size of D, A, and R ($|D|, |A|, |R|$) are determined by the experimental design. The group means, however, are not prespecified in order to ensure feasibility of the various configurations. Thus, we have one equation with 3 unknowns. However, from Table 5-16, we have the following:

$$\bar{A} = 0.5 * \overline{D}$$

$$\bar{R} = \bar{A}$$

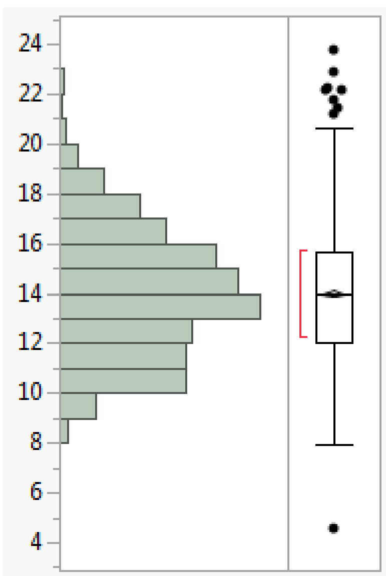
Now we have a system of three unknowns in three equations. For any given $|D|, |A|,$ and $|R|$, then, we can solve for the group means ($\overline{D}, \bar{A}, \bar{R}$).

Once $\overline{D}, \bar{A},$ and $\bar{R}$ are determined for a system configuration, we draw the process times for each group from a triangular distribution specific to that group. The upper and lower limits of each triangular distribution are determined from $\overline{D}, \bar{A},$ and $\bar{R}$ according to the relationships specified in Table 5-16. The mode of each distribution is calculated from the property of a triangular that mean $= \frac{\min + \max + \text{mode}}{3}$.

Once all times are drawn for a day, we scale them equally so that the total ASP processing time across all patients is equal to the prespecified day length of 7.5 hours. In scaling each process time, we ensure that it does not exceed the max or the min of its triangular distribution.

5.8.3 Method of Generating Discharge Process Times

Based on the retrospective 2015 dataset from the inpatient unit, we calculated the characteristics of the discharge completion times at the unit displayed in Figure 5-7.



Quantiles

100.0%	maximum	23.75
99.5%		21.5836
97.5%		19.238
90.0%		17.312
75.0%	quartile	15.67
50.0%	median	13.92
25.0%	quartile	12.05
10.0%		10.708
2.5%		9.718
0.5%		8.7252
0.0%	minimum	4.57

Summary Statistics

Mean	13.989225
Std Dev	2.5450035
Std Err Mean	0.0705044
Upper 95% Mean	14.12754
Lower 95% Mean	13.85091
N	1303

Figure 5-7: Statistics of the Inpatient Discharge Completion Time of Day at the Unit in 2015

The discharge processing time in our model is defined as the total time to complete the discharge of the patient, from midnight until the patient leaves the unit. This includes all processing and waiting, regardless of source. Discharge completion times can be used as a proxy for this discharge processing in our model. However, the discharge processing in our model is defined as being separate from the ASP processing time. We were unable to obtain any data on the contribution of the ASP to the total discharge completion time. Thus, we assume that the mean of the completion times is shifted by the mean of the ASP process time for discharge patients in our model.

We also want to ensure both realism and feasibility of the generated scenarios. We address the realism by preventing any discharges from occurring before 8 am (start of day on unit, after nursing huddle/rounds). We address feasibility by preventing any discharges from occurring after the end of the day (midnight, hour 24). Based on the above distribution, we further refined this end-of-day concept and limited the discharges from occurring beyond 8 pm (hour 20), resulting in a more symmetrical distribution.

To achieve these goals, we assume that the discharge processing time in our model follows a triangular distribution with minimum of 8, mean of 13.989 (mean of discharge completion times) minus the assigned mean ASP processing time of the discharge patients (derived according to the formula in the preceding section), and maximum of 20 minus the assigned maximum of the ASP processing time of the discharge patients. The mode for this triangular can then be derived.

$$Discharge\ Process\ Time \sim Triangular(8, 3(13.989 - \bar{D}) - (8 + 20 - 2\bar{D}), 20 - 2\bar{D})$$

For non-home discharge patients, after ASP processing time has been assigned, a feasibility check is made to ensure that their minimum possible discharge completion time (ASP process time plus discharge process time) is less than the non-home cutoff of 3 pm (15 hours). If it exceeds 15, then the discharge process time is redrawn for that patient until the minimum discharge completion time is below 15.

6 CONCLUSIONS

6.1 Summary

The quality of the US healthcare industry does not correlate with the high costs of healthcare in the US relative to other developed countries. Systems engineering, tested and proven in other industries such as manufacturing and distribution, has great potential in addressing key medical decision making and logistical problems along the US healthcare continuum. In this research, we focused on the challenges faced at acute care hospitals (ACH). Care at an ACH is intensive, the challenges are complex, and implications on patient safety and healthcare costs are severe. Within ACHs, the inpatient units (IUs) are the primary methods of care delivery; logistical inefficiencies here have significant consequences for the rest of the hospital.

While a patient's care in an IU spans multiple decision points over time, the final discharge is a highly critical logistical point. Inefficient or poorly executed discharge planning affects not only the care of the patient in question, but also the care providers, the rest of the IU, other upstream units, the emergency department, and potentially other hospitals and external facilities. With this in mind, we employed systems engineering principles to three key challenges in discharge planning:

(1) <u>Disposition determination/discharge initiation</u>: How can non-home discharges be identified, soon after admission, in order to initiate early planning and avoid potential delays?

(2) Day-of-discharge unit target strategies: What target strategies for inpatient discharge effectively reduce upstream patient boarding?

(3) Care provider patient prioritization: How should patients be sequenced for an ancillary service provider to minimize upstream patient boarding while satisfying current patient needs?

In this dissertation we addressed these three research areas, which formed the three contributions of this work.

6.1.1 Disposition Prediction (Contribution 1)

Non-home discharges, e.g., patients discharged to rehab, nursing homes, or long-term-care facilities, typically require more resources and planning than home discharges, due to the increased clinical and logistical complexity of such cases. Thus, accurate early identification of a patient as a future non-home discharge would allow for the planning to be initiated sooner in the patient's stay and potentially reduce the risk of unnecessary delays (impacting length of stay). We proposed an approach that would first identify the key factors available within 24 hours of admission that predict discharge disposition and then a method to convert that into an easy-to-understand and use scoring tool for the inpatient staff. We developed this using retrospective data from Boston VA medical center. Accordingly, we developed a multivariable logistic regression model to first identify key demographic, clinical, and historical factors associated with increased likelihood of non-home discharge for a general medicine patient. These factors included several aspects of a patient's care history often used by providers in practice. Our final model performed quite well on both training and testing datasets (AUC = 0.75 and 0.74, respectively). We then developed a scoring tool that used standardized coefficients and an optimization approach to identify scores associated with each significant factor. This tool was 84% correlated with our logistic regression model probabilities, and at an appropriate threshold value it achieved 82% sensitivity and 48% specificity on the testing dataset. We implemented this score in a sheet-based questionnaire-type tool for use in practice.

In practice, our tool would provide an early warning to differentiate the eventual home discharges (typically requiring less logistical planning) from the non-home (typically requiring days of planning), allowing for appropriate discharge planning to be initiated from Day 1 of the patient's stay. Care managers could begin to compile lists of external facilities, initiate discussion with the patients and their families, and contact insurance companies. Therapists could begin developing rehabilitation plans accordingly with the patients, or work with them to avoid such an outcome. In the case of false positives, the result would be an unnecessary increase in effort on the part of the care providers; however, our experience is that the benefit of avoiding costly potential discharge delays generally outweighs this.

6.1.2 Unit Target Strategies for Daily Inpatient Discharges (Contribution 2)

Better synchronization of inpatient discharges with upstream patient arrivals can greatly increase hospital flow and bed utilization and decrease patient boarding and diversion to other hospitals. To address this issue, we proposed an approach to model the inpatient day-of-discharge and its effects on upstream patient boarding, and a generic target strategy (*n*-by-*T)* that can be used by any unit to increase early discharges and mitigate upstream boarding. In a study with a trauma unit at Kettering Medical Center, Dayton, OH, we developed a discrete-event simulation which predicted up to 2-hour earlier shift in average discharge time and corresponding 15% reduction in upstream boarding; these results were corroborated by a pilot of our target strategy at the unit. Our approach and results were verified, through a simulation study, for a neurology unit at Maine Medical Center, Portland, ME; further such evaluations at other units and hospitals will help generalize the applicability and benefits of our proposed n-by-T strategy.

Our proposed n-by-T strategy provides inpatient units with a fairly straightforward goal: discharge n patients by the Tth hour. The individual units can develop procedures to achieve this target in a manner that best suits their dynamics, patient population, and practices. Since this target strategy only applies to a small number of discharges, it would also be easier to implement than other strategies (e.g., 'discharge by noon') that typically require a major change in practice for all discharges (such as having physicians write all discharge orders earlier in the morning, or decreasing the discharge process length). While any new long-term policy would require buy-in from the unit and some cultural change, our strategy could easily be combined with ongoing lean improvements and initiated as a key performance indicator for the unit.

6.1.3 Daily Patient Sequencing for Ancillary Service Providers (Contribution 3)

Some members of an inpatient discharge decision-making team are typically labeled as ancillary, such as care management or therapy, but they play important roles in determining and executing the logistical concerns associated with the discharge. Such providers, on a daily basis, must try to prioritize discharges in order to improve unit bed flow and reduce upstream patient boarding without neglecting the needs of the other patients they are responsible for. Ad hoc approaches to sequence the patient workflow often lead to missed due-dates and increased upstream boarding times. To address this challenge, we developed a model of a typical workload day for a general ancillary service provider (ASP) assigned to an inpatient unit and proposed an approach to generate patient sequencing strategies to assist these providers in meeting these goals. We constructed a scenario-specific MIP model and employed this model in a sampling based optimization approach paired with a simulated annealing meta-heuristic to derive practical, implementable, and understandable strategies that are robust to system variability. An experimental evaluation of our approach in collaboration with Maine Medical Center, Portland, ME, suggested several possible near-optimal strategies (average 13% deviation from optimal) for a variety of system configurations considered in our design. Other simpler strategies sometimes used in practice were compared to ours and could only perform better at the cost of constraint violations.

From a practical standpoint, we provide several key insights to ASPs, such as the importance of a system-level view when sequencing discharges for the day. We also provide general strategies that are easy to understand and implement; they take the form of rules that an ASP can follow in practice. These strategies do not require any calculations or integration with hospital legacy systems. We also offer a comparison with other strategies that ASPs may use and the trade-offs involved with each.

6.2 Future Work

6.2.1 Enhancements to the Early-Warning Tool

In this study, we were limited in our access to data and were unable to include several factors such as a patient's marital status, level of social support, and activities of daily living. Future work should include these and other relevant factors for which data could be collected. We also used the billed diagnosis at discharge as a proxy for the admitting diagnosis; future work may use actual admitting diagnosis if available for a more accurate representation of the clinical condition of the patient.

Another extension of our work would be to consider other classification approaches. While we used logistic regression due to its applicability to our problem and acceptance in medical practice, other more complex classification schemes such as discriminant analysis, support vector machine, or decision trees may outperform logistic regression on our problem. A future study could use these approaches on our dataset and compare their predictive performance to that of our regression model.

We classified patients into two broad categories: home or non-home. Future work could consider predicting discharge dispositions in more detail (home: home or home with home health care; non-home: nursing home, transfer to another hospital, rehabilitation center). In this case, other classification methods that are better suited to multinomial responses should be considered.

In practice, our score would need to be prospectively validated before it could be implemented. A pilot at this general medicine unit, and other units and hospitals, may help generalize our findings.

6.2.2 Refinements to the *n*-by-*T* Strategy

Several extensions could be made to our model of a typical day-of-discharge on an inpatient unit. Such extensions could consider the effects of patient discharge disposition on discharge processing time, or could differentiate by day of week, week of month, or month of year. Future work could also incorporate more accurate data for some of the factors we had to estimate, such as room cleanup time and delay for transportation services.

A natural progression of our study would be a direct comparison to the common practice of ‘discharge by noon,’ which aims for all discharges for the day to be completed by noon. It has been argued in the literature and practice that this strategy is overly aggressive, and that quantitative evidence is lacking to understand its actual impact at the unit and on upstream boarding. Our approach is well suited to examining such a strategy, and n-by-T may provide a more feasible alternative.

While we have begun to examine the generalizability of our model and strategy, it still remains a two-hospital study. In order to truly evaluate the generalizability, future work should consider other units and other hospitals.

6.2.3 Extensions to the ASP Patient Sequencing Problem

Several assumptions in our proposed model for ASP sequencing could be relaxed. For example, our model could include potential blocking of the ASP by other services that may result in waiting times before the ASP sees a patient in the optimal sequence. Alternatively, a compliance factor could be added to our model to evaluate the effect of ASP conformity to the optimal sequence. Other considerations include the following: extensions to multi-ASP and/or multi-unit systems; treatment of patient needs as multiple objectives rather than hard constraints; dynamic ASP decision-making throughout the day with the addition of new patients over the day; separate modeling of in-room and out-of-room ASP tasks; and consideration of different unit occupancy rates. The generalizability of our results to other services, units, and hospitals are also worth investigating.

In order to evaluate the practical usefulness of our work, a pilot would be required. In such a pilot, several practical considerations would need to be taken into account, such as identification of the ASPs, classification of the patients into the defined categories, selection of strategies for days not conforming directly to any of the configurations we considered, provision for situations when the suggested sequence could not be followed due to system constraints, and feedback on the success of the strategies. Long-term support and buy-in from the unit in assisting the ASP to adhere to the daily sequence would be necessary.

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