Day-of-Discharge Planning at Acute Care Hospitals

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DAY-OF-DISCHARGE PLANNING AT ACUTE CARE HOSPITALS

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Engineering

By

Kylie Machelle Bertsch
B.S., Wright State University, 2013

2014
Wright State University
I HEREBY RECOMMEND THAT THE THESIS PREPARED UNDER MY SUPERVISION BY Kylie Machelle Bertsch ENTITLED Day-of-Discharge Planning at Acute Care Hospitals BE ACCEPTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF Master of Science in Engineering.

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ABSTRACT

Bertsch, Kylie. M.S.Egr., Department of Biomedical, Industrial and Human Factors Engineering, Wright State University, 2014. Day-of-Discharge Planning at Acute Care Hospitals.

Hospitals provide a complex array of services to patient populations with highly variable conditions, needs, and preferences. These services are delivered with limited resources, and therefore, the synchronization of patient flow between various units in the hospital is essential for minimizing patient delay and congestion. Unfortunately, patient flow optimization is a topic in its research infancy, and, in current practice, hospitals struggle with the numerous ramifications of delays in care provision and increased costs.

Emergency Department (ED) crowding and boarding have become a topic of increased interest as the ED becomes an increasingly popular entry point to acute care hospitals. A key factor to these issues comes from the lack of available beds within the inpatient units to which newly admitted patients can be transferred. The inpatient day-of-discharge process plays a vital role in synchronizing supply with demand as the inpatient beds are released and made available to arriving bed requests.

The objective of this study was to reduce inpatient discharge lateness and overnight stays for patients being released from inpatient units and to alleviate patient boarding in upstream units. Alternative strategies for discharge order writing time and discharge process length were evaluated to identify strategies that had the greatest impact on advancing discharge completion time and reducing upstream boarding.

We collected both observational job shadowing and retrospective patient data
from a trauma unit at a local acute care hospital. Job shadowing helped us gain an in-depth understanding of the day-of-discharge process. The retrospective data contained elements on bed requests, order writing times, and discharge completion times, which helped us understand the underlying statistical distributions that drive process variability. This information was used to build a discrete event simulation (DES) model of the day-of-discharge process for the unit. Outcomes analyzed in the model were inpatient discharge completion time and upstream patient boarding time. After the model was validated with real hospital data, we evaluated three general categories of alternative strategies for a total of nine specific alternative strategies. Statistical comparison of outcomes showed that all nine had a significant effect on advancing discharge completion time and reducing upstream boarding time ($p < 0.05$).

Results showed that strategies combining both discharge order writing time and discharge process length (referred to as $n$-by-$T$) had the greatest impact on measured system outcomes. In the $n$-by-$T$ strategy, “$n$” is a set number of inpatients (e.g., 1 or 2) to be discharged by time “$T$” (e.g., 10 a.m. or 12 p.m.). Variations of this strategy indicated 25-40% reductions in upstream boarding time.

This research can be explored further in several directions. Analysis of the impact of seasonality and trends in occupancy rate, patient arrivals, and discharge times could be studied based upon day of the week, week of the month, and month of the year. An in-depth consideration of the components composing the day-of-discharge process such as physical therapy, occupational therapy, laboratory work, and transportation would add greater detail to the model. Incorporating discharge prioritization and provider workload optimization will allow for a comprehensive approach to inpatient discharge planning.
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This thesis is dedicated to the memory of my father, James M. Bertsch.

“Keep moving forward.”
**INTRODUCTION**

The U.S. spends over 17% of the GDP (over $2.5 trillion annually) on healthcare, with hospital care accounting for over 30% of this spending. Despite these extraordinary costs, the U.S. ranks last in five health outcome areas - quality, efficiency, access, equity, and support for healthy living (Davis et al., 2010). Hospitals provide a complex array of services to patient populations with highly variable conditions, needs, and preferences. These services are delivered with limited resources so that organization and synchronization of patient flow is essential for minimizing patient delay and congestion. Unfortunately, workload optimization for streamlining inpatient flow is a topic in its research infancy, and, in current practice, hospitals struggle with the numerous ramifications of inpatient waiting and congestion, such as emergency department crowding (Powell et al., 2012). This is especially true of the discharge process, a complex, multi-step process.

Discharge process planning ideally begins as soon as a patient enters into the hospital system. An understanding of the patient condition and necessary care, anticipated length of stay, patient needs upon discharge, and where the patient will go upon discharge are just a few of the numerous questions to be answered for each patient (Shepperd et al., 2013). As the patient’s health state improves and inpatient care comes to a completion, the key focus becomes the day-of-discharge process to release the patient from the inpatient unit. The bed formerly occupied then becomes available for new
patients arriving to the hospital through other upstream units (e.g., emergency department, PACU) and inter-hospital transfers.

This day-of-discharge process is a multi-step process with various steps to be coordinated depending upon factors specific to the patient (Farris et al., 2010). Our experience via job shadowing at a local hospital revealed that the medical staff must be aware of physician rounding patterns, order writing times, and final nursing care that needs provided. Varying number of support services, such as physical therapy, occupational therapy, and laboratory work, must also be completed dependent upon the patient type. Social workers and case managers work to arrange transportation from the hospital and make preparation for the disposition location the patient will go to. This involves many factors including capacity constraints at non-home locations, and insurance and paperwork approval and processing, which can all cause delays to the patients discharge from the inpatient unit.

When smooth coordination of this day-of-discharge process fails to take place, it delays bed release, which further leads to delays throughout the hospital. This affects the transfer of newly admitted patients from the ED – a significant and growing entry point (East et al., 2013) – PACU, SICU, etc., into the inpatient beds. Note that, after an inpatient bed request from an upstream unit has been made, a patient must wait in that unit until a bed in the inpatient unit becomes available. If there is a lack of availability in the inpatient unit, the patient will likely continue to board in that unit, sometimes up to several hours depending upon how soon the inpatient bed is released (i.e., a patient discharged and bed cleaned). This boarding, while waiting for an empty inpatient bed, in turn affects the capacity of the upstream unit holding the patient. For instance, in the ED
newly arriving patients who have not yet been admitted, or possibly even seen, are left to wait in the waiting area until resources become available causing significant crowding.

With inpatient flow pathways having such a great impact on hospital operations and delays, care coordination on intra-organizational operations within the acute care hospital setting is of great interest. Inpatient discharge lateness and possible overnight stays, along with patient boarding in upstream units are frequently encountered leading to suboptimal care access and quality. Through the understanding and data gathered in this study, we not only develop insights into which factors seem to impact discharge planning (in particular, day-of-discharge planning), but also evaluate the benefits of a few strategies to speed up discharges of patients deemed ready for discharge on a given day.

We first discuss patient pathway, discharge planning, and day-of-discharge process before discussing the problem statement, research objectives, and our contributions.

### 1.1 Patient Pathways

An admitted patient can take numerous paths throughout their care in the acute care hospital facility, see Figure 1. Patients entering an acute care hospital may have a direct pathway into an inpatient unit through an elective surgery or their severity upon arrival at the ED. Other patients may eventually flow into an inpatient unit from other sources including direct admits, transfers, ED after further observation, PACU, among others.
Figure 1: Patient flow through an ACH (Crawford, 2012)
As determined by the distinct patient condition and needs, many transfers may occur internally within the hospital. A surgical patient may enter through the ED, or may be elective, and then visit to the operating room (after pre-op), PACU, and floor before being discharged. In contrast, a medical patient typically enters through the ED (and very rarely as elective) and then may visit an ICU before being moved to the floor and eventually discharged. Throughout the inpatient stay, the patient not only receives necessary medical care, but plans are also being made on when and how the patient will be discharged from the hospital.

1.2 Discharge Planning

Discharge planning refers to the decision making process required to release a patient from one care facility to the next. Every inpatient discharge involves four critical decisions: 1) the timing of discharge, 2) the discharge process, 3) the location of patient disposition, and 4) the post-discharge follow-up. The planning of patient discharges is complex, and is typically influenced by patient-, provider-, and system-related factors. These decisions concerning patient discharges tend to be highly variable and, when suboptimal, they could result in increased readmissions and emergency department (ED) crowding. For instance, poor discharge planning accounted for 82-delay-related hospital days annually and $170,000 in annual costs, where 22% of reported delays were related to discharge planning (Srivastava et al., 2009). Ineffective care transition into disposition locations is often associated with this poor discharge planning (IHI, 2011). One in 5 Medicaid patients are readmitted within 30 days of the discharge, accounting for a
spending of over 17.4 billion annually (Jencks et al., 2009). ED crowding occurs when the demand for emergency services exceeds the number of resources available both in the ED and inpatient units (Hoot and Aronsky, 2008). ED crowding contributes to long wait times for patients, ambulance diversion, and ED boarding, which refers to patients continuing to utilize an ED bed while waiting on an available bed in an inpatient unit (Schull et al., 2003). According to a national survey, 91% of sampled ED staff responded that crowding was an issue (Institute of Medicine, 2007).

Within the discharge process, a multi-disciplinary discharge team, often composed of physicians, nurses, social workers, and case managers, work to get this patient off the unit and to their discharge location. This discharge planning ideally spans a patient’s entire stay at the inpatient unit, starting from when they enter the unit and continuing throughout their stay at the unit. As a part of the discharge process, various support services such as laboratory work, physical therapy, and occupational therapy are involved to satisfy each patient’s needs. All of these services must be successfully accomplished (and often in a prescribed order) before a patient is discharged from the unit (and the hospital). Almost always, the corresponding room and bed must be cleaned before it is made available to a patient waiting (and many times, boarding) in an upstream unit.

1.3 Day-of-Discharge

While the overall discharge planning is very broad and spans across multiple days of inpatient stay, we focus on the day-of-discharge process for a patient who has been
determined medically ready to leave the unit. On this day-of-discharge, the multi-
disciplinary discharge team, often composed of physicians, nurses, social workers, and
case managers, work to get this patient off the unit and to their discharge location.
Although this discharge planning ideally spans a patient’s entire stay at the hospital, the
day-of-discharge process becomes especially vital in getting the patients off the unit in
order for the previously occupied bed to be cleaned and made available to the next patient.

There are many key pieces that must be in order before a patient can be discharged
from an inpatient unit (IU). A key piece is that discharge orders must be completed by a
physician or physician’s assistant giving approval that the patient is ready to be
discharged. Also as a part of the discharge process, various support services such as
laboratory work, physical therapy, and occupational must be completed, as shown in
Figure 2. Another aspect of the discharge process is the social worker’s responsibilities in
arranging transportation, getting insurance approvals, and finding availability in
discharge disposition locations (skilled nursing facility, rehab facility, etc.), if applicable.
All of these must be accomplished in order before a patient can leave the hospital and the
bed is cleaned and made available to the next patient.
With so many factors to consider for each patient case, the day-of-discharge process for each patient must be handled meticulously. Some patient cases may be considered very simple with minimal amounts of support services required (e.g., expedited patients in Figure 2). However, a large number of inpatients deemed-ready-for-discharge requires several support services to be completed before they can be discharged from the unit. There are also the extreme cases that must be considered that cause the greatest amount of resource burden and bottleneck patient flow in the hospital. These are the complex cases where many support services are required as well as more complicated social service work that must be done in finding and getting the patient into their discharge disposition. A common cause of the extreme discharge process times is associated with patients needing to be discharged to a skilled nursing facility. There are often capacity constraints at these locations and several days may elapse before a bed is available for the patient to be discharged from the inpatient unit and transferred to this location. All of these case types must be considered when studying the day-of-discharge process and its effects on discharge timing and upstream boarding.
1.4 Problem Statement

ED crowding and boarding have become a topic of increased interest as the ED becomes an increasingly popular entry point to acute care hospitals. A key factor to these issues comes from the lack of open beds within the inpatient units to admit patients into. The inpatient day-of-discharge process plays a vital role in releasing these inpatient beds in a timely manner, hour of day, and making them available to arriving bed requests in an effort to synchronize supply with demand.

In the trauma unit studied at a local hospital for this project, the data from January to December 2013 indicated that the peak time when discharges were completed was often in the afternoon, around 4:00 p.m. However, inpatient bed requests arrived throughout the day, starting much earlier in the day. This resulted in an average boarding time of 145 min ($\sigma = 133$ min, range: 7 – 897 min) for patients before reaching the inpatient unit. Large amounts of variability in boarding time were also seen among the different hours of the day, as shown in Figure 3. Lower boarding times were typically observed in the early morning and late evening hours. These observations formed the basis for our analysis in examining the effects of key parameters within the day-of-discharge process on discharge timing in an acute care hospital (ACH) setting.
The goal of this study was to evaluate the effects of inpatient day-of-discharge process length and physician order writing time on discharge completion time and patient boarding in upstream units. We used a validated discrete-event simulation model to analyze the effects of several alternative day-of-discharge strategies on the two key system measures (discharge completion time and upstream boarding time).

1.5 Research Objectives

We now summarize the key objectives of this research:

- Analyze inpatient data and current day-of-discharge process at a local hospital to identify and understand the likely factors responsible for delays in inpatient discharge.
- Conduct a simulation study to model the interrelationship among these factors and validate this model using real hospital data.
• Evaluate alternative day-of-discharge strategies and their effect on discharge completion time and upstream patient boarding time. These strategies include the following:
  o decreased discharge process time with less variation
  o earlier physician order writing times
  o completion of “n” number of discharges by a pre-specified time “T” in the day

• Provide specific recommendations to the inpatient team (trauma unit in our study) on the impact of adjusting key variables within their day-of-discharge process.

1.6 Contributions of Research

The contributions of this research are several, as indicated below:

• This research provides insight into the day-of-discharge process at ACHs. Several factors are identified that affect day-of-discharge planning, including order writing, number of required support services, transportation arrangements, and disposition location capacity. Some of these factors are shown to have a significant impact on discharge completion and upstream boarding times.

• We take advantage of Discrete Event Simulation (DES) methodology to model the day-of-discharge process. Such systems-level modeling and quantification is vital when implementing and/or altering the inpatient workflow. It also helps conduct what-if analysis to predict future behavior when system parameters vary from the norm. Our analysis found that the alternative n-by-T strategy, which requires modifying both the discharge order writing time and discharge process length, could result in up to 40% reduction in boarding time (which is over 1,800 bed hours of increased availability in
upstream units).

- Additionally, this work provides information of the effects on several key variables in the day-of-discharge process that an acute care hospital can use to strategize the most impactful changes in their system. The insights gained from this study were shared with the local hospital’s inpatient throughput leadership team and trauma unit department heads and physicians, who were all highly receptive. Further discussions towards the study’s beneficial results corresponding to hospital throughput goals and possible ways to pilot $n$-by-$T$ strategy (especially 2-by-12) within several inpatient units confirmed the potential impact of the study’s results in a practical setting.

1.7 Thesis Outline

The remainder of this thesis is organized as follows. Relevant literature pertaining to discharge planning and hospital crowding is reviewed in Section 2. In Section 3, the inpatient discharge process, analyzed data, and a description of the logic behind the overall model is presented. Section 4 describes the model results and comparisons of outcome measures for the alternative strategies. Finally, Section 5 summarizes the results and discusses the direction for future research.
LITERATURE REVIEW

This chapter summarizes academic literature relevant to our study on the day-of-discharge process. This literature presents information based upon discharge planning, ED crowding and resource management, and modeling healthcare with simulation.

2.1 Day-of-Discharge Planning

The patient discharge process is complex and requires many different discharge team members input, including physicians, nurses, case managers, and social work. There are many key parts of the process that vary among patients but the results of the process have impacts spanning the entire hospital flow. There have been a number of pieces of literature studying the discharge process and potential ways to make improvements. Studies on a more comprehensive approach to the patient discharge process and needed follow-up have also become an area of interest. We summarize only the relevant studies in both the medical and IE/OR literature.

In the medical literature, Manning et al. (2007) studied the use of assigned discharge appointments for patients. A four month study period was conducted using the discharge appointments. Results showed the 60% of patients were discharged within 30 minutes of their scheduled time. No information was gathered on the impact of discharge appointments on patient satisfaction and health outcomes during the study.
Jack et al. (2009) studied the impacts of using the ReEngineered Discharge (RED) program. The program involved providing medication instructions and follow-up appointment arrangements for patients to be discharged. Follow-up 2 to 4 days after discharge by a clinical pharmacist was also conducted to reiterate the discharge plan. Patients involved in the study reported feeling more prepared for discharge and had lower hospital utilization rates than those not involved in the RED group.

The detrimental impacts of insufficient discharge planning have been seen through retrospective studies. Srivastava et al. (2009) studied a tertiary-care children’s hospital for patient delays that occurred. Through the study, it was found that poor discharge planning accounted for up to 82 delay-related inpatient days (9% of total inpatient days) and $170,000 in excess costs. They found that nearly 25% of patients during the study could have been discharged earlier than their actual discharge time.

Vermeulen et al. (2009) studied admission to discharge ratio for Toronto area hospitals for a 3-year period. Admission to discharge ratio over the study period fell to 0.6 or below and resulted to an 11 minute average ED LOS decrease the next day. A ratio of 1.3 to 1.4 led to a 5 minute average ED LOS increase the next day. They also found that weekend ratios had a larger impact on next day ED LOS than the ratios on weekdays. They concluded that by better balancing admission to discharge ratio, the amount of time spent waiting by patients and ED boarding could be reduced.

Wong et al. (2009) used historical data from a Toronto hospital to study the impact of smoothing patient discharge throughout the week on the number of ED beds occupied by inpatients. System dynamics modeling was used to show that smoothing inpatient
discharges over the entire week, including weekends, reduced ED beds occupied by inpatients by 27-57%. It was also seen that ED LOS for patients also decreased by 7-14 hours.

Dobson et al. (2010) used a stochastic modeling method to model patient bumping within an ICU. The effect of discharging patients early when ICU capacity was limited was modeled using different arrival patterns and capacity parameters. They found that elective surgery schedules do have an impact on the number of patients bumped in the ICU. In this study, they showed the tradeoffs between capacity and surgical schedules have on patient bumping in the ICU.

Powell et al. (2012) utilized a cross-sectional computer modeling analysis of data from Northwestern University’s Feinberg School of Medicine for weekly admissions and discharges in September 2007. The study was used to find how earlier discharges of patients have an effect on ED patient boarding. By shifting the peak inpatient discharge time four hours earlier, the ED boarding time was reduced from the baseline of 77 hours per day to 0 hours. They also found that discharging 75% of patients by noon or by discharging all patients by 4:00pm reduced the total boarding from 77 hours to 3 hours.

In the IE/OR literature, Kreke et al. (2008) modeled the decision making process for discharge of patients with sepsis. The process was modeled as an unconstrained Markov Decision Process. Non-stationary control limit policies were derived from the model. Farris et al. (2010) conducted a case study on a 362-bed teaching hospital in Texan. Methods such as task and functional flow analysis were used to identify steps in the current patient discharge process and the major causes of delay to discharge. They
concluded there is a need for healthcare engineering methods to create scheduling for the discharge process which could assist in reducing discharge delays.

Chan et al. (2012) studied the impact of various discharge decisions in the ICU on patient readmissions. A discharge decision support tool was created to assist in the decision of when to discharge a patient from the ICU based upon readmission risk. They found that ICU patient admission delays may have an effect on the LOS and patient outcomes. They also determined that the use of the discharge decision support tool could help reduce the number of readmitted patients.

Shi et al. (working paper) used stochastic network modeling and simulation studies with data from a major public hospital in Singapore to gain insight on reducing ED boarding time through inpatient flow management. The study evaluated several operational policies for patient wait times and overflow strategies. The analysis found that a policy incorporating an initial discharge peak between 8:00 a.m. and 9:00 a.m., 26% of patients discharge before noon, and steady allocation delays all day.

The inpatient discharge process, with a specific focus on day-of-discharge, has proved to be an important piece of the hospital inpatient flow. This downstream piece of inpatient flow is both influenced by and influences upstream units within the hospital. These upstream units are the places where patients arrive to the hospital and will wait to be admitted to an inpatient unit if necessary. A key hospital entry point that is directly affected by this downstream discharge process is the emergency department, which we will focus on in the following section.
2.2 Emergency Department Crowding and Resource Management

Emergency departments increasingly serve as an entry point to the hospital (Burt and McCaig, 2006, East et al., 2013), feeding in to the downstream inpatient units when admissions are necessary. This increased volume with limited number of ED resources has caused ED crowding to become a serious issue in hospital patient flow. Effects include numerous hours of boarding, overworked staff, and even patients leaving without being seen. With such a wide-spread problem occurring, resource management of beds and hospital staffing has been explored to help face the ED crowding issues.

Hoot and Aronsky (2008) completed a broad literature review including 93 articles related to the causes, effects, and solutions of ED crowding. Main causes found through their review included inpatient boarding, inadequate staffing, non-urgent visits, and bed shortages. They found that delays in care, patient mortality, and ambulance diversion were all among the main effects of ED crowding. Many of the prominent solutions to the crowding issue included crowding measures, capacity planning, and non-urgent referrals.

Cochran and Bharti (2006) studied the bed utilization for inpatient units at a 411 bed, 13 tertiary unit hospitals. Through queuing analysis and discrete-event simulation bed usage was balanced and maximized flow through the modeled system was analyzed. By their study, they found that improved management of bed capacities in the hospital helped to reduce patient wait times.

Capacity planning with non-stationary queuing models to reduce the number of patients who leave without treatment has also been studies by Green et al. (2006). Arrival
data to the ED was collected over two 39 week periods, one prior to any change in staffing and the other with staffing changes. The study showed that a 12 hour increase in staffing per week reduced the number of patients who left without being seen by 22.9%. They concluded that staffing plans based upon patient arrival patterns may significantly reduce the number of patients who leave without being seen.

Queuing networks are another approach that has been explored for use in hospital resource management. Cochran and Roche (2009) use this model to study hospital capacity requirements based upon patient acuities and non-homogenous arrival patterns. They use patient acuity to split the patient flow. Patients with a low acuity level go to an area separate from patients with a higher acuity level.

Allon et al. (2009) described patient flow between the ED and inpatient units with a queuing network model. The model showed that both ED and inpatient bed capacity had an important effect on time spent on ambulance diversion when considering the size of the hospital. An ED that is large in relation to the size of the hospital showed greater impact from inpatient boarding. If the ED is small in relation to the size of the inpatient units, ED capacity had a greater impact on the number of diversion hours.

Khare et al. (2009) use computer simulation to model a large urban hospital. Their study focused on the impact of ED bed capacity increases, increases in patient admittance rates, and increases in number of patients visiting the ED. They found that an increase in the number of ED beds increased the mean length of stay by 7 minutes. An increase in admittance rate decreased the mean length of stay by 22 minutes. Increases in the number of patients visiting the ED gave similar results to the base scenario. They conclude that
improvements to the patient boarding would be more impactful on reductions in the ED length of stay than increases in ED bed capacity.

2.3 Modeling Healthcare Processes with Simulation

Healthcare systems are complex and dynamic in nature. Because of this, the use of computer simulation models to study these systems has flourished as a beneficial tool. Discrete-event simulation has provided a means to model the changes of a system over time and the state of variables within the system (Law, 2007). While mathematical programming of this type of system is highly difficult and unable to capture the dynamic pieces in the systems, DES provides a useful way to model and analyze these processes.

Jun et al. (1999) conducted an extensive literature review of 117 articles related to applying discrete-event simulation in health care. The review included using models for improving and optimizing patient flows and routing, resource allocation, capacity planning, and staff planning. More recent review of the use of computer simulation in healthcare can be found by Eldabi et al. (2007) and Mielczarek and Uzialko-Mydlikowska (2010).

Jacobson et al. (2006) provided an overview of discrete-event simulation applications in health care systems. The review demonstrated how discrete-event simulation has become a preferred methodology for modeling complex, dynamic systems in health care due to the increased pressures for health care organizations to provide quality, efficient, cost-effective care.
Key performance measures have also been studied through the use of discrete-event simulation. Ruohonen et al. (2006) conducted a study to investigate the impact of a triage-team on system outcomes. This team was composed of a doctor, nurse, and receptionist working together to better assess and assign priority and treatment to patients. Through the multiple scenarios tested, the team showed up to a 26% reduction in throughput time for patients in the hospital system.

Other areas explored through the use of discrete-event simulation modeling are resource allocation and capacity planning. Duguay and Chetouane (2007) focused their study on resource allocation of physicians, nurses, and examination rooms as a means to reduce inpatient waiting times. A discrete-event simulation model was created and several alternative scenarios were evaluated for their impact on key performance measures. Through their evaluation, it was found that adding one additional nurse and physician between 8:00am and 4:00pm showed the greatest improvement on output measures.

Facility planning can also be explored through the use of discrete event simulation. Ashby et al. (2008) analyzed the challenges of moving an existing facility’s inpatient volumes into a new facility with a smaller capacity. A discrete event simulation model was utilized to study the effects of moving the current system from a larger facility to a smaller one. Results showed that a lower number of inpatient beds had a negative effect on upstream ED boarding time and patient flow through the hospital. However, the study also found that decreases in non-value added procedures, the use of conditional orders, and the use of discharge lounges and general inpatient units would allow for the ED to operate more smoothly in a facility with reduced capacity.
Discrete-event simulation in healthcare can also be used as a forecasting tool. Hoot et al. (2008) utilized simulation to forecast ED conditions for 2, 4, 6, and 8 hours into the future. The study looked at key performance measures including number waiting, waiting time, occupancy level, length of stay, and ambulance diversion. It was found that forecasting performance measures in the ED was possible through the modeling of patient flow in the department.

Patient experience in an emergency department was studied using a simulation-based framework. Abo-Hamad and Arisha (2012) use an interactive simulation-based decision support framework to explore healthcare process improvement. A balanced scorecard (BSC) is used within the tool to support improvement using key performance measures. The framework was implemented in an ED in an adult-teaching hospital in Dublin, Ireland. Several alternate scenarios were evaluated including having no admission blockage to inpatient units, increasing the number of beds in the ED, adding one physician, and many of the combinations of these alternatives. Their results showed that reducing the blockage to inpatient units had a larger impact on the key performance indicators than just increasing ED capacity or staffing.

Clearly, DES methodology has received wide acceptable in the healthcare systems engineering and medical domains owing to the past successes. In our study, we use DES to study the effects of physician order writing time and discharge process length on inpatient discharge completion time and patient boarding time in upstream units. Our research adds to the existing literature focusing on analyzing the effects of discharge timing on key performance indicators. We evaluate three alternative discharge strategies and their impact through the use of DES.
3 MODEL DESCRIPTION

Building upon the past work in modeling inpatient flow at an acute care hospital (Crawford et al., 2014), our study focused on the day-of-discharge process at an inpatient unit. Our collaborating hospital requested we focus on their specialized trauma unit for this project. The model included the main elements for the day-of-discharge process at this unit along with new bed requests made to the unit. We employed a discrete-event simulation (DES) approach to model patient flow from upstream hospital units into an inpatient unit. The outcomes of interest were patient boarding in upstream units and inpatient discharge lateness due to their impact on patient flow, quality of care, and patient satisfaction levels. A baseline model was created to simulate the current state of the day-of-discharge process from the unit. Additionally, nine alternative strategies were developed to evaluate their impact on discharge completion time and boarding time in upstream units. This section will discuss data collection, the current day-of-discharge process, modeling and validation, and design of alternative discharge strategies.

3.1 Data Collection

Data and process understanding play a key role in the development of an accurate, validated, simulation model. In our study, we used two modes of data collection: job shadowing to gain process flow understanding and retrospective patient data to understand system inputs and outcomes.
3.1.1 Job Shadowing

Prior to the development of a simulation model, an in depth understanding of patient flow to inpatient units and the inpatient discharge process had to be established. Through job shadowing at the local hospital and extensive literature review, we developed a process map depicting the day-of-discharge process for inpatients from the trauma unit, as shown in Figure 4.

This figure shows the complexity of the process and the involvement of many different key staff members in the inpatient discharge process. A multi-disciplinary team composed of nurses, physicians, social workers, and case managers must not only provide the proper medical care, but also work to have a discharge plan in action and work towards getting the patient off the unit in a timely manner. This multi-disciplinary team meets at least twice each day in order to monitor the patients on the unit and specifically focus on those who are medically ready, or nearly ready, to be discharged from the unit. The team must ensure that all the vital pieces are completed to induce a timely discharge: e.g., discharge orders written, patient education, medication reconciliation and instructions to patient, physical/occupational therapy, insurance approvals, availability at disposition location, and transportation arranged. The bed then must be cleaned by the hospital cleaning staff only after which it becomes available in the electronic health system (e.g., EPIC) to allow the transfer of a patient (in an upstream unit) with an outstanding bed request.
Discharge Planning begins as soon as the patient arrives at the floor—estimated discharge data—discharge location

Orders must include:
- Post-op care
- PT/OT instructions
- Medication care instructions
- Prescriptions given

Discharge Barriers:
- Consults (neuro-exceptally) may take up to 1 day
- Transportation issues (waiting on family members)
- PT/OT
- Acceptance into care facility
- Insurance issues

Figure 4: Process map of trauma unit discharge process
3.1.2 Retrospective Patient Data

We used 2013 data from a local hospital’s trauma unit to model patient bed requests, number of inpatient discharges per day, discharge process length, time of physician orders, and the resulting boarding. Data was analyzed from one year of patient information. Because of the variability of patient data across hour of day, day of week, and month of year (see Figure 5), the input data was based upon an “average” day derived across all the days of available hospital data.

![Figure 5: Bed requests and inpatient discharges by day of week](image)
Another consideration of the current system was to gain an understanding of the departments where bed requests typically come from. These departments would experience the greatest impact on boarding time due to implementation of alternative strategies. Figure 6 shows that the Emergency Department, Surgery, Medical Surgical Intensive Care Unit (MSICU), and Surgical Intensive Care Unit serve as the most common upstream units for the trauma unit.

![Bar chart showing bed requests by department]

Figure 6: Bed requests by department

Discharge disposition, or location patient is discharge to, also plays an important role in the discharge process. Information on the discharge disposition for the analyzed hospital data is shown in Figure 7. Our study does not take into consideration delays and other factors specific to discharge disposition. This type of analysis could be conducted in future work.
Figure 7: Inpatient discharges by disposition

Figure 8 shows the rates of completed discharges versus bed requests. It is evident that there is a lack of synchronization of these two patterns, with the discharge complete time peaking much later in the day than bed requests. Because of this, patients board in the upstream units for several hours (after bed request has been placed) before bed becomes available.
3.2 A Discrete-Event Simulation Model

Our simulation model was developed using ARENA v14 (Rockwell Automation, Wexford, PA). This model captured patient flow from upstream units into the inpatient (trauma) unit. Bed requests were allowed from all other hospital units.

The number of inpatient beds modeled each day is based upon the number of inpatients to be discharged that day. Once a patient is determined to be discharged that day, they continue through the steps of the discharge process until reaching release from the inpatient bed. Once an inpatient bed becomes available, a patient who has submitted a bed request and had been boarding then takes possession of the bed.

The baseline model was built using data collated from a local acute care hospital. Figure 9 depicts a high level flow chart of the simulation model. Our model simulates a
24-hour period starting at midnight during which inpatients are discharged and bed requests occur. The top half of the flow chart depicts the day-of-discharge process for discharging inpatients. The simulation starts by initializing the system with the number of discharges to occur during that 24 hour run. The patients are then assigned a physician order writing time. Once the order writing time has elapsed, the patient then moves into the discharge process. This stage includes an aggregated time accounting for all the things that must be completed before a patient can leave the inpatient unit including items such as physical therapy, occupational therapy, and arranging medical equipment.

Once a patient has completed the discharge process, they are discharged from the inpatient unit. The inpatient bed is only made available after the bed cleanup time has elapsed. The now clean bed is available for a patient that is currently boarding or for the next bed request arrival.

The bottom portion of the flow chart depicts the bed requests in the simulation model. These bed request patients are held until an inpatient bed becomes available and then transported to the unit. The available inpatient bed is then seized.
3.2.1 Assumptions

Several important assumptions were made in developing our simulation model including:

1. An “average” day is modeled across the entire year of patient data, without considering trends for day of week, week of month, month of year, etc.
2. Unit occupancy rate of 95% for each replication (to simulate peak times when boarding becomes an issue for inpatient throughput).
3.2.2 Input Data

Input data made available by the hospital was used to obtain statistical distributions of inputs for use in the DES model. These inputs include number of discharges per day modeled as $\text{POIS}(4.91)$ inpatients, discharge order writing time modeled as $\text{NORM}(13.28, 2.76)$ hours in time of day, bed cleanup time modeled as $\text{NORM}(1.5, 0.115)$ hours, and bed requests modeled as non-stationary Poisson process. Given the limited overnight staffing in the unit and slight variations in the process, we modeled the transportation time to inpatient unit before 7 a.m. as $\text{TRIA}(0.5, 1.5, 3)$ hours, and transportation time to inpatient unit as $\text{TRIA}(0.5, 0.75, 1.75)$ hours.

Because of the skewness of the hospital data for discharge process length (skewness > 2), we were unable to fit a standard distribution to represent the hospital data accurately. We, instead, used the underlying empirical distribution in the model to simulate discharge process time.

Table 1 provides a summary of input data for the simulation model. These data elements are the controls for the model to be manipulated through the evaluation of alternative strategies.
3.2.3 Model Verification and Validation

The main performance measures considered in the simulation model are patient boarding time in upstream units and discharge completion time. Patient boarding time was measured from the time a bed request was placed until the time that patient was transferred to an available inpatient bed. Discharge completion time was based on the process an inpatient must go through prior to leaving the hospital, including physician order writing and the discharge process length assigned as model input data.

Validation of the model included face validation of the expert members of the team, verification to ensure correct data analysis and input in correspondence with the model’s specifications, and external validation to confirm the simulated values reasonably matched the provided hospital data.
Each replication length was 24 hours in length, run 1,000 to capture system variability. To meet the 95% occupancy rate, the number of inpatient beds available each day was modeled to equal the number of patients discharged that day plus one additional “free,” bed to be seized upon the first bed request.

Validation measures for the model included the time the discharge process was completed for inpatients and the boarding time for patients who placed a bed request (see Figures 10-11, Tables 2-3). Because the sample data exhibited skewness values above 2, we used a non-parametric test to test if the samples (actual and simulated) came from the same distribution. The Mann Whitney U test provided a $p$-value of 0.643, not giving evidence to reject that the samples come from different distributions. The distribution of time to complete the discharge process time had a symmetric distribution (skewness < 0.25) so we employed a $t$-test for comparison purposes. This test provided a two-tail $p$-value of 0.4365 providing no evidence to reject that the samples came from the same distribution.
Figure 10: Hospital data vs model output (boarding time)

Table 2: Hospital data vs model output (boarding time)

<table>
<thead>
<tr>
<th></th>
<th>KHN Data</th>
<th>Simulation Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>2.41</td>
<td>2.54</td>
</tr>
<tr>
<td>Std Deviation</td>
<td>2.22</td>
<td>2.51</td>
</tr>
<tr>
<td>95% Confidence Interval</td>
<td>2.41 ± 0.06</td>
<td>2.54 ± 0.04</td>
</tr>
<tr>
<td>Mann Whitney U Test p-value</td>
<td></td>
<td>0.643</td>
</tr>
</tbody>
</table>
Figure 11: Hospital data vs model output (discharge complete time)

Table 3: Hospital data vs model output (discharge complete time)

<table>
<thead>
<tr>
<th></th>
<th>KHN Data</th>
<th>Simulation Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>16.16</td>
<td>16.21</td>
</tr>
<tr>
<td>Std Deviation</td>
<td>2.41</td>
<td>2.64</td>
</tr>
<tr>
<td>95% Confidence Interval</td>
<td>16.16 ± 0.06</td>
<td>16.21 ± 0.04</td>
</tr>
<tr>
<td>t-test p-value</td>
<td>0.437</td>
<td></td>
</tr>
</tbody>
</table>
3.3 Modeling Alternative Discharge Strategies

Based upon the process mapping, initial data analysis, and validation process, we identified key variables that seem to impact the day-of-discharge process at the trauma unit. We chose to focus our alternative strategy designs using two variables: discharge process length and discharge order writing time. The following sections describe our approach to model and evaluate these variables individually, as well as an alternative strategy considering both variables together.

3.3.1 Discharge Process Length Strategy

In the original process and retrospective data, a high average process length and large variation ($\mu = 3.2$ hr, $\sigma = 2.3$ hr) was observed in the time from when discharge orders were placed until the time an inpatient was discharged from the inpatient unit.

As discussed in earlier chapters, the day-of-discharge process is complex with many support services potentially involved. These support services, such as the laboratory and physical therapy, are also responsible for servicing many other units throughout the hospital. Each support service has its own process of managing the case load of patients that must be seen each day. In our analysis of alternative strategies for the discharge process, we assumed that there would be a methodology implemented to help prioritize day-of-discharge patients for these support services. We do not comment on the details of how these should be executed within the hospital, but would rely on internal quality and improvements teams to formulate a practical plan based upon the needs of the unit and hospital.
Considering this, we focused on evaluating the effects of decreasing the discharge process time. Discharge process lengths were modeled using an empirical distribution from the hospital data with restrictions on the longest duration for discharge process allowed (4, 5, and 6 hours). This restriction on extreme discharge process length provided a way to decrease the average and standard deviation of the process time. For the three alternative strategies in this category, we evaluated: i) $\mu = 2.1 \text{ hr}, \sigma = 1.0 \text{ hr}$, ii) $\mu = 2.4 \text{ hr}, \sigma = 1.2 \text{ hr}$, and iii) $\mu = 2.6 \text{ hr}, \sigma = 1.4 \text{ hr}$.

### 3.3.2 Discharge Order Writing Time Strategy

Another variable considered for alternative strategy design was the effects of changing the discharge order writing time. In the current data set, we observed that discharge order writing had a mean time of 1:18 p.m. ($\sigma = 2.75 \text{ hr}$). Since some of the main steps of the day-of-discharge process happen only after the discharge orders are placed, we focused on exploring what effect it would have on the outcome measures if the order writing time was shifted earlier in the day.

The order writing patterns within the trauma unit are unique in comparison with some of the other hospital units, such as general surgery or general medical unit. Typically, trauma surgeons are responsible for initiating the discharge process. These surgeons typically round early in the morning, perform surgeries throughout the day, and have other administrative and education duties. Sometimes they are able to round again in the afternoon to complete any unfinished process on their end and to help discharge patients ready for that day. Unfortunately, because of the varying levels of priority faced by the
trauma surgeons, quite often the discharge orders are not written until the afternoon. This delay is the first step of the discharge process needed to be addressed. While orders are not allowed to be written the night before, there are several approaches to move order writing times earlier in the day. One option is to have proactive identification of patients to be discharged the next day and ensure that in the early morning rounds, all information is in place for the discharge orders to be written. Another possibility to explore is the use of a designated physician’s assistant during the morning hours to support the order writing process to ensure that orders are completed in a timely manner.

While we did not want to propose to the hospital specific alternatives, we did want to evaluate what if the order time was advanced by 1 or 3 hours. This was implemented by adjusting the mean and standard deviation of the normal distribution (used to model input data on order writing time), while maintaining the same coefficient of variation. For example, the Baseline model utilized a normal distribution with \( \mu = 13.28 \text{ hr}, \sigma = 2.76 \text{ hr.} \) (with coefficient of variation, C.V., equal to 0.21). The alternative strategy of shifting order writing time by 3 hours meant that \( \mu = 10.28 \text{ hr} \) and the corresponding standard deviation would be C.V.\( \ast \mu = 2.16 \text{ hr}. \) The resulting distribution for a 3-hour advance in order writing time became NORM(10.28, 2.16). We applied the same approach for the 1-hour advance, which resulted in NORM(12.28, 2.55).

### 3.3.3 n-by-\( T \) Strategy

The final category of alternative strategies we designed was an approach that considered both discharge order writing time and discharge process length. This strategy
was influenced from knowledge of previous models that have been piloted in a clinical setting at a different hospital and is what we consider an $n$-by-$T$ strategy.

The $n$-by-$T$ strategy ensures that “$n$” number of patients determined to be discharged that day will have orders written and the discharge process completed by “$T$” (time of day). For example, 1-by-12 denotes one inpatient to be discharge from the inpatient unit by 12 p.m. Likewise 2-by-10 denotes two inpatients to be discharged by 10 a.m. each day. To model this strategy, a decision is made after the day of discharge patients have been generated in the model to place $n$ discharges on a path to complete their discharges by $T$. These discharges are assigned a discharge completion time based upon the model input TRI(8, 9, 10) when $T = 10$ a.m. and TRI(9, 10.5, 12) when $T = 12$ p.m. This input parameter is based upon expert opinion and previous models that have been piloted in a clinical setting at another hospital. All remaining patients follow the default pathway as discussed in the Baseline model.
4 ANALYSIS AND RESULTS

In Chapter 3 details on data collection and model development, verification, validation, and alternative strategy modelling were described. We now report results obtained from the evaluation of alternative strategies on the key system outcomes.

4.1 Results

Using the validated simulation model, we obtained system outcomes for each of the alternative strategies. The main outcomes focused on in this study included discharge completion time and upstream boarding time. The results from evaluating these alternative strategies on each of the outcome measures are displayed in Tables 4 and 5.

Table 4 shows the effect of each of the nine alternative strategies in comparison with the Baseline (current system) model on discharge completion time. The first column of the chart lists the name of the strategy evaluated, with the second column providing which of the three main categories the strategy belongs to. The following columns provide details on the mean, standard deviation, and median of the discharge completion time. Mean and median are given in hour of the day (24-hour time), while standard deviation is given in number of hours. A 95% confidence interval on the mean is also provided.
The final column in Table 4 provides a $p$-value for each of the alternative strategies, using the Baseline model as a reference. We found that each of the nine alternative strategies had a statistically different discharge completion time ($p$-value < 0.05). The comparison of each alternative strategy on Discharge Completion Time was found by using the t-test. For example, it can be seen that the 2-by-12 strategy shifts the mean discharge completion time to approximately 2 p.m. from the Baseline model mean of approximately 4 p.m.
Table 5 shows the effect of each of the nine alternative strategies in comparison with the Baseline (current system) model on upstream patient boarding time. A $p$-value (using Mann Whitney U test) is given for each of the alternative strategy to demonstrate that each was statistically different than the Baseline model in determining the boarding time outcome.

Table 5: Alternative strategy results (boarding time)

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Median</th>
<th>95% Confidence Interval</th>
<th>$p$-value</th>
<th>% Reduction in Boarding Time</th>
<th>Time Reduction in Bed Hours (per patient /annually)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline model</td>
<td>2.57</td>
<td>2.53</td>
<td>1.47</td>
<td>2.57 ± 0.038</td>
<td>Reference</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>2-by-12</td>
<td>1.70</td>
<td>1.55</td>
<td>1.17</td>
<td>1.70 ± 0.024</td>
<td>&lt; 0.0001</td>
<td>33.85%</td>
<td>0.87 / 1566</td>
</tr>
<tr>
<td>1-by-12</td>
<td>1.94</td>
<td>1.79</td>
<td>1.26</td>
<td>1.94 ± 0.027</td>
<td>&lt; 0.0001</td>
<td>24.51%</td>
<td>0.63 / 1134</td>
</tr>
<tr>
<td>2-by-10</td>
<td>1.55</td>
<td>1.32</td>
<td>1.12</td>
<td>1.55 ± 0.020</td>
<td>&lt; 0.0001</td>
<td>39.69%</td>
<td>1.02 / 1836</td>
</tr>
<tr>
<td>1-by-10</td>
<td>1.86</td>
<td>1.67</td>
<td>1.23</td>
<td>1.86 ± 0.026</td>
<td>&lt; 0.0001</td>
<td>27.63%</td>
<td>0.71 / 1278</td>
</tr>
<tr>
<td>Orders Completed 1 hr Earlier</td>
<td>2.34</td>
<td>2.32</td>
<td>1.39</td>
<td>2.34 ± 0.035</td>
<td>0.0002</td>
<td>8.95%</td>
<td>0.23 / 414</td>
</tr>
<tr>
<td>Orders Completed 3 hr Earlier</td>
<td>1.94</td>
<td>1.94</td>
<td>1.23</td>
<td>1.94 ± 0.030</td>
<td>&lt; 0.0001</td>
<td>24.51%</td>
<td>0.63 / 1134</td>
</tr>
<tr>
<td>Discharge Process Length $[\mu = 2.6\ hr, \sigma = 1.4]$</td>
<td>2.41</td>
<td>2.41</td>
<td>1.38</td>
<td>2.41 ± 0.036</td>
<td>0.0007</td>
<td>6.23%</td>
<td>0.16 / 288</td>
</tr>
<tr>
<td>Discharge Process Length $[\mu = 2.4\ hr, \sigma = 1.2]$</td>
<td>2.34</td>
<td>2.3</td>
<td>1.38</td>
<td>2.34 ± 0.035</td>
<td>0.0002</td>
<td>8.95%</td>
<td>0.23 / 414</td>
</tr>
<tr>
<td>Discharge Process Length $[\mu = 2.1\ hr, \sigma = 1.0]$</td>
<td>2.29</td>
<td>2.27</td>
<td>1.36</td>
<td>2.29 ± 0.034</td>
<td>&lt; 0.0001</td>
<td>10.89%</td>
<td>0.28 / 504</td>
</tr>
</tbody>
</table>
More insightful interpretation of the results on the effects of the alternative strategies on boarding time is given in the last two columns of Table 5. This is given first as a percentage of reduction in boarding time of each strategy in comparison to the baseline. The impact on boarding time is also given in the final column in the table showing the time reduction in bed hours per patient and annually (based upon 1800 patients per year as observed in the hospital data). For example, the 2-by-12 strategy has a significant reduction in bed hours; 0.87 hours per patient or over 1500 hours annually at the upstream units.

It can be seen from the previous tables that the \( n \)-by-\( T \) strategies were the most impactful on boarding time reduction. This is because these strategies guarantee that approximately 20\% (approximately 1 patient discharge out of 4.91 mean discharges, see Table 1) or 40\% (approximately 2 patients discharges) would occur each day by 10 a.m. or 12 p.m. In the inpatient unit analyzed, approximately 2.5\% of discharges occur by 10 a.m. and 10\% by 12 p.m. Table 6 shows the percentage of days per year where the situation demonstrated in the \( n \)-by-\( T \) strategies was met in the analyzed year. As such, when it is guaranteed that these scenarios are met every day, it is to be expected that discharge time lateness would be reduced as well as alleviating upstream boarding time.

<table>
<thead>
<tr>
<th>Inpatient Unit (current system)</th>
<th>% of days requirement met</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-by-10</td>
<td>4.93%</td>
</tr>
<tr>
<td>2-by-10</td>
<td>--</td>
</tr>
<tr>
<td>1-by-12</td>
<td>18.36%</td>
</tr>
<tr>
<td>2-by-12</td>
<td>2.19%</td>
</tr>
</tbody>
</table>
The reduction in discharge process length and variation showed the lowest overall impact on reducing boarding time out of the three alternative strategy categories. These results were supported by the acute care hospital’s process improvement team who had seen very little effect on the time discharges are completed when only the discharge process length was reduced during pilot studies at other units within the hospital.

4.2 Comparison of Alternative Strategies

The effects of each of the alternative strategies on discharge completion time are shown in the following graphs (Figures 12-14). The impact of reducing the average discharge process length and standard deviation is shown in Figure 12. It is observed that these alternative strategies have a low amount of impact on the discharge completion time against the current system. This is seen by the strategy providing the lowest amount of boarding time reduction in comparison to the other categories of alternative strategies.

The effect of shifting the discharge order writing times on the trauma unit are shown in Figure 13. The shift on the mean discharge order writing time has a significant effect on the discharge completion time. The mean discharge completion time shifts from an approximate mean of 4 p.m. to approximately 2 p.m.
Figure 12: Discharge complete time: Discharge process length vs Baseline

Figure 13: Discharge complete time: Discharge orders strategies vs Baseline
The impact of the $n$-by-$T$ strategies is displayed in Figure 14. These strategies cause the pattern of discharge distribution to switch from a single mode to bi-modal. This is caused by the guarantee that 1 or 2 patients will be discharged prior to the set time each day. After $n$ have been discharged, the discharge process of the remaining patients is unaffected (following a distribution similar to the Baseline model).

![Graph showing discharge complete time for different strategies vs Baseline]

Figure 14: Discharge complete time: $n$-by-$T$ strategies vs Baseline

To identify statistically significant differences between alternative strategies, Tukey’s test was conducted on the discharge completion time outcomes. The results indicated that some alternative strategies evaluated result in statistically similar results (denoted by the same letter), while others resulted in statistically different discharge times (denoted by different letters).
In summary, all of the evaluated alternative strategies had a significant impact on the discharge completion time and upstream boarding time. Changes in discharge completion length provided the smallest effect on system outcomes. Shifting order writing time an average of 1 or 3 hours earlier in the day also showed significant improvements on the system outcome measures. The $n$-by-$T$ strategy demonstrated the greatest impact on both discharge completion time and upstream boarding time. This is because this strategy takes into consideration changes in both the discharge process length and order writing time.
The insights gained from this study were shared with the local hospital’s inpatient throughput leadership team and the trauma unit department heads and physicians. The leadership team was highly receptive to the results of the simulation model evaluating alternative strategies on the trauma unit. Further discussions towards the study’s beneficial results corresponding to hospital throughput goals and possible ways to pilot $n$-by-$T$ strategy (especially, 2-by-12) within units confirmed the potential impact of the study’s results in a practical setting.
SUMMARY AND FUTURE RESEARCH

The goal of this project was to understand the inpatient day-of-discharge process within a trauma unit at an acute care hospital and the impact of various alternative strategies on inpatient discharge process outcome measures. The objectives were to reduce inpatient discharge lateness and overnight stays for inpatients being discharged, as well as alleviating patient boarding in upstream units.

We created and validated a discrete-event simulation model of the day-of-discharge process and bed requests on an inpatient trauma unit. Using this model, we analyzed the relationship between physician order writing time and the discharge process length on discharge completion time and upstream patient boarding. We modeled the discharge process time as an aggregation of all required components and their sequence for a patient to be discharged from the unit.

The simulation model assisted in analyzing the impact of three types of alternative strategies for the day-of-discharge process, for a total of nine alternatives. Each of the alternative strategies was found to significantly advance discharge completion time \((p < 0.05)\). The results showed that the \(n\)-by-\(T\) strategies that guarantee a set number of patients out by an earlier time in the day showed the greatest impact on upstream patient boarding time.

The simulation model presented in this research models the patient flow during
the day-of-discharge process from an inpatient trauma unit as well as the simultaneous bed requests from upstream units that happen each day. While our model is structured around the processes of a trauma unit, we recognize that processes on different specialized inpatient units may differ in nature. Our model can be adapted to compensate for these variations in the day-of-discharge process dependent upon the modeled unit.

5.1 Managerial Insights

Analysis of the system outcomes showed that the discharge completion time and associated upstream boarding are affected by the physician order writing time and discharge process length.

The strategies with the greatest potential effects on the system outcomes evaluated in our study were the $n$-by-$T$ strategies. They provided the overall largest impacts on moving average discharge completion time earlier in the day along with the greatest percentage reductions in boarding time. Up to one hour of bed time per patient (or up to 1800 bed hours annually) were reduced through the evaluation of the alternative strategies. This amount of reduction in bed hours, which can in turn open beds for new patients, would likely have significant impact on inpatient throughput.

The implementation of a variation of this strategy on an inpatient would require a proactive discharge approach. Many pieces of the discharge process must be in order to ensure that the desired number of patients is out by the determined time. One approach would be identifying patients who will be the early discharges the evening before. This would allow the physicians or physician assistants to have their orders ready, nurses to
finish any medical care, transportation arrangements made, and all support services to be scheduled and complete by the desired time.

Another factor for the multi-disciplinary discharge team to consider in selecting patients to be an early discharge patient is the number of outstanding factors or services needed to be completed prior to discharge. A patient with numerous support services outstanding or with barriers with insurance paperwork may be more difficult to discharge early in the day. However, a patient with minimal support services and more simplistic transportation arrangements may be a more ideal candidate to discharge during this morning period.

We recognize that the inpatient day-of-discharge process is a very complex, dynamic process dependent upon many variables. The practical implementation of our evaluated strategies assumes many pieces of the discharge process to be arranged in an appropriate manner to ensure patient discharge by the desired time.

5.2 Future Research Opportunities

It would be advantageous to conduct further analysis on trends and seasonality of occupancy rate and arrival and discharge trends. A great deal of variation can occur between days of the week, weeks of the month, and months of the year. Various factors such as weather, peaks of recreational activities, seasons for specific sicknesses, and insurance functionalities, among many other items, can influence the occupancy at an acute care hospital. Analysis of trends in patient data would allow these changes in occupancy to be added into the model.
Other areas of interest in studying the day-of-discharge process would be to investigate the impact of having a day with an above average number of discharges to be conducted from an inpatient unit on the time discharges are complete and boarding time. Also the impact of the disposition location on day of discharge time and upstream unit on boarding time could be studied.

For this study, data for support services and other details of specific patient discharge processes were unavailable. This caused us to treat the inpatient discharge process length as an aggregation of these components. In the future, when data on support services is available and able to be studied in further detail, the model can be expanded to consider each of these processes.

The day-of-discharge process from inpatient units in an acute care hospital is a complex process. Numerous members of a multi-functional discharge team along with support services are all integral parts in ensuring proper care and release of a patient from the inpatient units. Our research presents a simulation model capable of accounting for some of these factors and their effect on boarding time of patients in upstream units throughout the hospital. Through our study, several alternative strategies related to physician order writing time and discharge process length have been evaluated for their potential impact and improvement of system outcomes.
6 REFERENCES


