EMERGENT INPATIENT ADMISSIONS AND DELAYED HOSPITAL DISCHARGES

By

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ABSTRACT

Emergency Department (ED) congestion can be better understood by examining overall system impacts, in particular inpatient admissions and discharges. This study first investigates trends of inpatient admissions, volume of patients in the ED who have been admitted (ED “boarders”), length of stay, and bed resources of three major admitting services at our teaching institution. It was found that patients admitted to the General Internal Medicine (GIM) service constituted the majority of ED boarders by default rather than design, as GIM served as a safety net for specialty services. This study investigates operational factors that impact discharge and found that day of the week and holidays followed by team organization and scheduling are significant predictors of daily variation in discharge rates. Based on these results, next, a system dynamics computer simulation was built to test the impact of various discharge smoothing strategies on the number of ED boarders. Next, this study uses the framework and tools of system dynamics methodology to design a conceptual model of the ED boarder problem that may be used as a generalizable roadmap to create sustainable improvements in ED congestion. Finally, this study introduces a novel real time metric of hospital operational discharge efficiency—daily discharge rate—to bring focus on the underlying causes of discharge variation and help indicate opportunities for improvement.
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Table of Contents

Abstract .......................................................................................................................... ii
Acknowledgements ........................................................................................................ iii
Dedication ......................................................................................................................... iv
List of Tables .................................................................................................................... vii
List of Figures .................................................................................................................. viii

Chapter 1: INTRODUCTION ......................................................................................... 1
1.1 BACKGROUND ON EMERGENCY DEPARTMENT-GENERAL INTERNAL MEDICINE (ED-GIM) ................................................................. 1
1.2 BACKGROUND ON SYSTEM DYNAMICS ......................................................... 3
1.3 THESIS HYPOTHESES AND DATA SOURCES .............................................. 8
1.4 THESIS OVERVIEW AND SYNOPSIS ................................................................ 9
1.5 RESEARCH CONTRIBUTION ............................................................................. 12

Chapter 2: UNDERSTANDING HOSPITAL AND EMERGENCY DEPARTMENT CONGESTION: AN EXAMINATION OF INPATIENT ADMISSION TRENDS AND BED RESOURCES ........................................... 14
2.1 INTRODUCTION ................................................................................................. 16
2.2 METHODS .......................................................................................................... 18
2.3 RESULTS ............................................................................................................. 22
2.4 DISCUSSION ....................................................................................................... 31

Chapter 3: HOW MUCH DO OPERATIONAL PROCESSES AFFECT HOSPITAL INPATIENT DISCHARGE RATES? ........................................................................... 37
3.1 INTRODUCTION ................................................................................................. 38
3.2 METHODS .......................................................................................................... 41
3.3 RESULTS ............................................................................................................. 48
3.4 DISCUSSION ....................................................................................................... 54

Chapter 4: SMOOTHING INPATIENT DISCHARGES DECREASES EMERGENCY DEPARTMENT CONGESTION: A SYSTEM DYNAMICS SIMULATION MODEL ........................................ 59
4.1 INTRODUCTION ................................................................................................. 61
4.2 MATERIALS AND METHODS ............................................................................ 64
4.3 RESULTS ............................................................................................................. 71
4.4 DISCUSSION ....................................................................................................... 81
Chapter 5: USING SYSTEM DYNAMICS PRINCIPLES FOR CONCEPTUAL MODELLING OF PUBLICLY FUNDED HOSPITALS .......................... 87
  5.1 INTRODUCTION ................................................................. 88
  5.2 THE PROBLEM AS DESCRIBED BY THE HOSPITAL .......... 90
  5.3 BRIEF OVERVIEW OF SYSTEM DYNAMICS AND SYSTEM ARCHETYPES ......................................................... 91
  5.4 UNDERSTANDING THE PROBLEM ........................................ 3
  5.5 KEY CAUSAL RELATIONSHIPS .................................................. 97
  5.6 REDESIGN OF STRATEGIES ...................................................... 110
  5.7 RECOMMENDATIONS FROM THE CONCEPTUAL MODELLING PROCESS ................................................................. 116
  5.8 CONCLUDING REMARKS ....................................................... 119

Chapter 6: REAL TIME OPERATIONAL FEEDBACK: DAILY DISCHARGE RATE AS A NOVEL HOSPITAL EFFICIENCY METRIC ............ 120
  6.1 INTRODUCTION ................................................................. 121
  6.2 RATIONALE FOR MONITORING DAILY DISCHARGE RATE .... 123
  6.3 DAILY DISCHARGE RATE – A NEW INDICATOR TO SCREEN AND MONITOR DISCHARGE EFFICIENCY ................. 125
  6.4 CAVEATS FOR FRONTLINE MANAGERS CONSIDERING MEASURING DAILY DISCHARGE RATE .................. 135
  6.5 CONCLUSION ................................................................. 137

Chapter 7: SUMMARY ................................................................. 138
  7.1 IMPLICATIONS ................................................................. 138
  7.2 FUTURE RESEARCH ............................................................ 142

Appendix
  Supplemental Figure ............................................................ 144
  Model Equations ................................................................. 145
  References ................................................................. 155
# List of Tables

<table>
<thead>
<tr>
<th>Table 2.1</th>
<th>Emergency Department visits admitted to General Internal Medicine, Oncology, and Cardiology/Cardiovascular Surgery inpatient services at Toronto General Hospital, from 2004 to 2007.</th>
<th>23</th>
</tr>
</thead>
<tbody>
<tr>
<td>Table 2.2</td>
<td>Emergency Department visit volumes at Toronto General Hospital, from 2004 to 2007.</td>
<td>23</td>
</tr>
<tr>
<td>Table 2.3a</td>
<td>Admitting service of Emergency Department inpatient admission visits with cancer-related CMGs at Toronto General Hospital, from 2004 to 2007.</td>
<td>28</td>
</tr>
<tr>
<td>Table 2.3b</td>
<td>Admitting service of Emergency Department inpatient admission visits with heart-related CMGs at Toronto General Hospital, from 2004 to 2007.</td>
<td>28</td>
</tr>
<tr>
<td>Table 2.4</td>
<td>Inpatient staffed beds and midnight bed census at Toronto General Hospital and Princess Margaret Hospital, from 2004 to 2007.</td>
<td>30</td>
</tr>
<tr>
<td>Table 3.1</td>
<td>General Internal Medicine patient and service characteristics.</td>
<td>49</td>
</tr>
<tr>
<td>Table 3.2</td>
<td>Univariate and multivariate analysis of operational factors on team discharge rates.</td>
<td>51</td>
</tr>
<tr>
<td>Table 4.1</td>
<td>Model validation.</td>
<td>76</td>
</tr>
<tr>
<td>Table 4.2</td>
<td>Scenario tests.</td>
<td>78</td>
</tr>
</tbody>
</table>
List of Figures

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure 1.1</td>
<td>The reduced set of four generic archetypes</td>
<td>5</td>
</tr>
<tr>
<td>Figure 2.1</td>
<td>Mean Emergency Department beds occupied at midnight by inpatients at Toronto General Hospital, from 2004 to 2007</td>
<td>25</td>
</tr>
<tr>
<td>Figure 2.2</td>
<td>Box plot showing median boarding length of stay of Cardiology/Cardiovascular Surgery, Oncology, and General Internal Medicine inpatient admissions at Toronto General Hospital, from 2004 to 2007</td>
<td>26</td>
</tr>
<tr>
<td>Figure 2.3a</td>
<td>Mean Emergency Department beds occupied at midnight by inpatients and median boarding length of stay for GIM at Toronto General Hospital for 2007 and 2008</td>
<td>34</td>
</tr>
<tr>
<td>Figure 2.3b</td>
<td>Mean Emergency Department beds occupied at midnight by inpatients and median boarding length of stay for total admitting services at Toronto General Hospital for 2007 and 2008</td>
<td>34</td>
</tr>
<tr>
<td>Figure 3.1</td>
<td>A typical four-week period for one of the admitting teams</td>
<td>45</td>
</tr>
<tr>
<td>Figure 3.2</td>
<td>Adjusted discharge ratios and 95% confidence intervals evaluating day of the week and holiday periods</td>
<td>50</td>
</tr>
<tr>
<td>Figure 4.1a</td>
<td>ED visit admission proportions to GIM in hourly slots, grouped by patient categories</td>
<td>66</td>
</tr>
<tr>
<td>Figure 4.1b</td>
<td>GIM discharge proportions in hourly slots, grouped by patient categories</td>
<td>66</td>
</tr>
<tr>
<td>Figure 4.1c</td>
<td>ED visit admission proportion to GIM (home category) in hourly slots, grouped by days of the week</td>
<td>66</td>
</tr>
<tr>
<td>Figure 4.1d</td>
<td>GIM discharge proportion (home category) in hourly slots, grouped by days of the week</td>
<td>66</td>
</tr>
<tr>
<td>Figure 4.2</td>
<td>Strategy for scenario testing</td>
<td>68</td>
</tr>
<tr>
<td>Figure 4.3</td>
<td>Percent GIM patient days versus percent GIM patient admissions for the various GIM patient categories</td>
<td>70</td>
</tr>
</tbody>
</table>
Figure 4.4  Simplified representation of the system dynamics simulation model structure…………………………………………………….. 72

Figure 4.5a Three functions derived from historical hospital data from the 2005 study period: Bed-Turn-Around Time…………………………………………………….. 74

Figure 4.5b Three functions derived from historical hospital data from the 2005 study period: Discharge from ED Probability…………………………………………………….. 74

Figure 4.5c Three functions derived from historical hospital data from the 2005 study period: Alternate Level of Care Occupancy…………………………………………………….. 74

Figure 4.6 Model output: GIM in ED for Scenarios “Smoothed Average Case” and “Every Day is a Weekday Case” applied to home discharges, compared with base case…………………………………………………….. 80

Figure 5.1 Main issues confronting hospital management ………………………… 95
Figure 5.2 Silver tsunami …………………………………………………………… 98
Figure 5.3 Reduction of capacity translates to higher acuity……………………… 98
Figure 5.4 Balancing budget…………………………………………………………… 100
Figure 5.5 Limits to revenue generation …………………………………………… 102
Figure 5.6 Dealing with ED boarders ………………………………………………… 104
Figure 5.7 Specialty services work around………………………………………… 106
Figure 5.8 Organizational excellence………………………………………………… 108
Figure 5.9 Patient-staff ratio strategies ……………………………………………… 108
Figure 5.10 Conceptual model of the ED-GIM problem ……………………………… 111
Figure 5.11 Opting out of emergent care exacerbates the ED-GIM problem……… 112
Figure 5.12 Inefficient operational processes exacerbate the ED-GIM problem.. 115
<table>
<thead>
<tr>
<th>Box 6.1</th>
<th>What is daily discharge rate?</th>
<th>126</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure 6.1a</td>
<td>Box plot showing median levels of average length of stay, by day of discharge (excludes left against medical advice and deaths) for the General Internal Medicine service, Toronto General Hospital from January 15th to December 15th for the two years, 2005 and 2006</td>
<td>127</td>
</tr>
<tr>
<td>Figure 6.1b</td>
<td>Box plot showing median levels of daily discharge rate, by day of discharge (excludes left against medical advice and deaths) for the General Internal Medicine service, Toronto General Hospital from January 15th to December 15th for the two years, 2005 and 2006</td>
<td>127</td>
</tr>
<tr>
<td>Figure 6.2a</td>
<td>Control charts for average LOS, on consecutive Mondays from January 15, 2005 – December 15, 2005 for the General Internal Medicine service, Toronto General Hospital</td>
<td>130</td>
</tr>
<tr>
<td>Figure 6.2b</td>
<td>Control charts for daily discharge rate, on consecutive Mondays from January 15, 2005 – December 15, 2005 for the General Internal Medicine service, Toronto General Hospital</td>
<td>130</td>
</tr>
<tr>
<td>Figure 6.3</td>
<td>Daily discharge rate versus average LOS. Each point represents a 6-month team-specific average for clinical teams of the General Internal Medicine service, Toronto General Hospital, from January 15th to December 15th for the two years, 2005 and 2006</td>
<td>133</td>
</tr>
<tr>
<td>Box 6.2</td>
<td>Day-to-day applications of daily discharge rate</td>
<td>134</td>
</tr>
<tr>
<td>Figure A1</td>
<td>Stock-flow diagram of the system dynamics simulation model constructed to evaluate smoothing of discharges over the course of the week</td>
<td>144</td>
</tr>
</tbody>
</table>
CHAPTER 1
INTRODUCTION

The purpose of this chapter is to provide background on the Emergency Department - General Internal Medicine (ED-GIM) problem and review the application of system dynamics methodology in health care. The thesis hypotheses will be presented and data sources will be described. Finally, an overview and synopsis of the thesis will be presented along with a statement of research contribution.

1.1 BACKGROUND ON EMERGENCY DEPARTMENT-GENERAL INTERNAL MEDICINE (ED-GIM)

Timely access to emergent patient care is an important issue that concerns Emergency Departments (ED) across Canada and around the world. Evidence has accumulated that congested EDs prolong wait times for care, decrease throughput, increase patients leaving without being seen by a physician, and have led to adverse events and staff and patient frustration (Baker et al., 1991; Aminzadeh and Dalziel, 2002; Arendts et al., 2006). Currently, Canadian EDs are functioning at or above peak capacity, severely limiting their ability to meet the demand for emergency care (Canadian Institute for Health Information, 2005; Abu-Laban, 2006; Li et al., 2007). Health care providers and hospital management recognize that ED congestion is a larger systemic issue (Derlet and Richards, 2000). Lack of available acute inpatient beds and downstream post-acute resources have been cited as significant factors that compromise ED throughput.
(Brewster et al., 2001; Dunn, 2003; Asplin and Magid, 2007; Canadian Institute for Health Information, 2007; Greene, 2007). There is general consensus that sustainable improvements in ED wait times require thoughtful system-wide consideration (Graff, 1999; Forster, 2005).

This study takes place at the Toronto General Hospital (TGH). As a teaching and tertiary care hospital specializing in transplantation and cardiac care, TGH faces a particularly challenging patient population. Like other teaching hospitals, TGH treats a high proportion of seriously ill patients and those with complex care needs (Andrulis et al., 1991; Ayanian and Weissman, 2002; Baker et al., 2004; Blank et al., 2005). In 2008, TGH received more than 32000 ED visits with nearly 20% or 6292 visits that required inpatient admission. The General Internal Medicine (GIM) inpatient service is the largest admitting service within TGH ED (Canadian Institute for Health Information, 2005, 2007). In 2008, GIM admitted over 45% (2944) ED inpatient admissions. The majority of patients admitted to GIM are elderly with multiple, complex medical illnesses. GIM expertise often overlaps with recognized medical subspecialty services (for example, Cardiology, Nephrology, Neurology) and as a result, GIM acts as a safety net for specialty services. However, when all beds on the GIM ward are occupied, admitted GIM patients stay in the ED, waiting from hours to days. Boarding in the ED is made worse when acute beds are blocked by patients who no longer require acute care and are awaiting placement in the community. Approximately 30% of TGH GIM patients require post-acute care in the community (long-term care, complex continuing care, convalescent care, rehabilitation care, home care, or palliative care), and are deemed
“alternate level of care” (ALC). ALC patients are a significant downstream contributor to ED congestion.

Work on this thesis began with the introduction of the Hospital Accountability Agreements (HAA) between Ontario hospitals and the Ontario Ministry of Health and Long Term Care. The 2005/06 planning cycle was the first year HAAs were used in Ontario. HAAs focus on quality improvement and a balanced approach to hospital performance with performance metrics in the domains of financial health, patient access and outcomes, organizational health, and system integration (Ontario Ministry of Health and Long-Term Care, 2007). For example, ED length of stay and percent ALC patient days are two performance metrics Ontario hospitals are held accountable for in the HAA. With the initiation of HAAs, transforming processes within ED and GIM are strategic necessities for UHN.

At UHN, clinical and managerial decision makers must consider the strategic and organizational aspects of their clinical services to meet HAA targets. This study, at its inception, was intended to encourage clinicians and hospital managers to view ED-GIM with a larger systems perspective. To this end, system dynamics methodology was used.

1.2 BACKGROUND ON SYSTEM DYNAMICS

System dynamics is a methodology that helps understand complex feedback systems over time. It represents dynamic systems with stocks, flows, feedback loops, and delays. Problems are rigorously diagnosed with causal loop mapping and dynamic
consequences are revealed via computer simulation. A brief description of the qualitative and quantitative modelling elements of system dynamics now follows.

**Causal Loop Mapping**

Causal loop mapping assists exploring, questioning, learning and commitment to a course of action. It requires the active participation of stakeholders to document their mental models and causal assumptions of the problem explicitly on paper. In this way, causal loop mapping provides a coherent structure for debate that is transparent to the participants and can help share and align piecemeal mental models.

At the core of causal loop diagrams are feedback loops and time delays. There are two basic types of feedback loops, positive or reinforcing loops and negative or balancing loops. Positive loops reinforce or amplify a given behaviour or event while negative loops balance or stabilize behaviours/events. A bank balance accumulating interest or an avalanche are examples of positive feedback loops, while a thermostat and predator/prey populations are examples of negative feedback loops.

Wolstenholme has proposed that all counter-intuitive behaviour or unintended consequences may be characterized using a generic two-loop archetype (Wolstenholme, 2003). One loop is the intended consequence feedback loop and the second loop is the unintended consequence feedback loop. A delay exists before the unintended consequence manifests itself and an organizational boundary ‘hides’ the unintended consequence from the ‘view’ of those initiating the intended consequences (Wolstenholme, 2004) (Figure 1.1). The intended and unintended feedback loops may be balancing or reinforcing, resulting in 4 combinations of the generic two-loop archetype:
Figure 1.1: The reduced set of four generic archetypes
1. “Underachievement” (Intended = reinforcing; Unintended = balancing)

   The intent is to reinforce the outcome, but the unintended consequence loop opposes or balances the outcome.

2. “Out of control” (Intended = balancing; Unintended = reinforcing)

   The intent is to control or stabilize the problem, but the unintended consequence loop reinforces the problem.

3. “Relative achievement” (Intended = reinforcing; Unintended = reinforcing)

   The intent is to reinforce the outcome, but this comes at a cost to another sector by reinforcing in the opposite direction for the other sector.

4. “Relative control” (Intended = balancing; Unintended = balancing)

   The intent is to control or stabilize the problem, but this comes at a cost to another sector by controlling in the opposite direction for the other sector.

**Computer Simulation**

Computer simulation models aim to describe dynamic consequences. Simulation attempts to reproduce events as they occur in the real world inside a computer program with the intent to test various operating strategies before real world implementation. Since the human mind is not well equipped to trace the dynamics of complex feedback structures, simulation can help to improve understanding of how entities interact over time and to analyze the long-term effectiveness of policies commonly used when managing them. From simulation, we can reach a new understanding of how the problem arose, altering our mental models and leading to the implementation of new policies, decision rules and strategies (Sterman, 2000).
In system dynamics simulation, entities are modeled as continuous quantities, rather like a fluid flowing through a system of reservoirs or tanks connected by pipes. Patients "flow" through a network along lines with specified "rates" (either constant or based on a formula) and accumulate at points called levels or stocks. Stocks characterize the state of the system and provide the basis for actions. Stocks absorb the differences between inflow and outflow, such as admission and discharge rates. As stocks vary, information about the size of the stock will feed back in various ways to influence the rates of inflow and outflow, altering the stocks and closing the feedback loops in the system. Policies, decision rules and strategies that apply in the real health care system can be represented and tested in the model. The model then feeds back outcomes (expected and unexpected) of real world decisions. This can be especially useful because alternative resource allocations and “what-if” analyses can be tested. The results of simulation help management better understand feedback, predict behaviour, and plan capacity.

Causal mapping and computer simulation mutually reinforce one another. Causal mapping provides a framework to elicit system description from stakeholders and generates a hypothesis for how the system created the troubling behaviour. It contributes useful insights to computer simulation by identifying structure and policies in the system under consideration. Creating and simulating a model contributes rigor and clarity to system description by revealing gaps and inconsistencies that must be remedied in the causal mapping of the system.

The tools of system dynamics have been extensively applied to solve important real world problems in health care. Applications of qualitative system dynamics mapping
models in health care include models for short-term patient flows (Coyle, 2000), acute patient flows (Wolstenholme et al., 2007; Lane and Husemann, 2008), and surgical patient flows (Lee et al., 2009). Applications of quantitative system dynamic simulation models include models for an Emergency Department (Lane et al., 2000; Lattimer et al., 2004), diagnostic laboratories (Rohleder et al., 2007), social care (Wolstenholme, 1999), waiting lists and public health issues (Homer and Hirsch, 2006; Leischow and Milstein, 2006; Hirsch et al., 2007). A review of system dynamics applications applied to health care issues are discussed in articles by Eldabi (Eldabi et al., 2007).

1.3 THESIS HYPOTHESES AND DATA SOURCES

Thesis Hypotheses

The thesis of this work is that inpatients occupying ED beds, particularly those admitted to GIM, are the primary cause of ED congestion at TGH. This thesis examines possible reasons why GIM volumes have increased in recent years, evaluates the impact of operational factors on GIM discharge rates, builds a simulation model of the ED-GIM system to test whether smoothing discharges over the course of the week reduces ED congestion, qualitatively maps common causal feedback loops found in publicly funded hospitals experiencing ED congestion, and proposes daily discharge rate as a novel metric of hospital operational discharge efficiency.
Data Sources

The main sources of data for this thesis are UHN’s primary patient care system Electronic Patient Record (EPR) for emergency department visits and the administrative information system WinRecs for discharged inpatients. The financial information system SmartStream was accessed to obtain inpatient bed staffing and midnight occupancy levels. Attending physician schedules, team admission schedules, and resident schedules were obtained from team rosters maintained by the GIM residency program. Details regarding the specific data elements used for each analysis are provided within the text of the individual thesis chapters. Qualitative data was kindly and generously provided by GIM and ED Staff Physicians, Nurse Managers, Allied Health teams, Transportation and Housekeeping Services, CCAC Co-ordinators, Hospital Resource Specialists in Discharge Planning, and the Hospital Utilization Manager.

1.4 THESIS OVERVIEW AND SYNOPSIS

This thesis has five major sections:

1) Describing recent emergent inpatient admitting trends and establishing its impact on the Emergency Department;

2) Evaluating hospital operational factors that affect daily discharge rate;

3) Developing a system dynamics computer simulation that incorporates admission and discharge dynamics for the purposes of testing scenarios aimed at reducing ED congestion;
4) Designing a conceptual model of the ED-GIM problem using system dynamics methodology with the aim of creating a generalizable roadmap to sustainable improvements in ED congestion;

5) Introducing a novel metric – daily discharge rate – as a real-time indicator of hospital inpatient operational efficiency;

The thesis is that ED congestion can be better understood by examining overall system impacts, particularly inpatient admissions. The intended audience includes care providers, health care administrators, policy makers across the different care sectors, and healthcare researchers within system dynamics and operational research communities. The ultimate goal of this thesis is to consider the interdependencies of system-wide impacts and deeper rooted cultural and organizational barriers to sustainable improvements in ED congestion.

CHAPTER 2. Understanding hospital and emergency department congestion: An examination of inpatient admission trends and bed resources. This chapter examines changing admitting patterns of three major admitting services and its effects on ED congestion. Analyses include inpatient admissions, ED boarding volumes, boarding lengths of stay, and inpatient bed resources over a four year period.

CHAPTER 3. How much do operational processes affect hospital inpatient discharge rates? This chapter examines the effect of hospital operational factors including day of the week, holiday, team call schedules, team rotation schedules, individual attending
physicians, and attending length of coverage on daily care team discharge rates over the course of a two year period.

CHAPTER 4. **Smoothing inpatient discharges decreases emergency department congestion: a system dynamics simulation model**. This chapter describes the formulation, validation and use of a computer simulation model designed to test whether smoothing discharges across the days of the week improves ED-GIM patient flow. Agreement between historical performance measures and model output, and results of various scenario tests applied to the model are presented.

CHAPTER 5. **Using system dynamics principles for conceptual modelling of publicly funded hospitals.** This chapter describes the process of taking the chronic ED boarder problem common to many publicly funded hospitals and from it designing a conceptual model to help clarify to hospital management why clearly intended policies and decisions do not always result in the desired behaviour.


CHAPTER 6. **Real time operational feedback: daily discharge rate as a novel hospital efficiency metric.** This chapter advocates the application of daily discharge rate as a real time measure of discharge efficiency capable of detecting variations in operational factors that affect discharge. The use of control charting is illustrated as an effective way to present daily discharge rate data to clinicians in real time to prompt actionable improvements in discharge efficiency.

CHAPTER 7. **Summary.** This chapter state the implications of this thesis, including the value of hospital operational data for comprehensive systems planning; the contribution of qualitative and quantitative modelling elements of system dynamics to hospital strategy; and the value of measuring daily discharge rate to focus improvement in operational efficiency. Additionally, this chapter outlines directions for future research in order to make thesis findings more generalizable.

1.5 **RESEARCH CONTRIBUTION**

There are three main contributions from this work:

- there is value in using hospital operational data for comprehensive systems planning
- both qualitative and quantitative modelling elements of system dynamics have potential pragmatic contributions to hospital strategy and decision making
- daily discharge rate is a novel real time metric of hospital discharge efficiency, sensitive to detect variations in operational factors that affect discharge
More generally, this thesis shows the ‘ED-GIM’ problem is neither an ED nor a GIM problem. GIM boarders in the ED are a symptom of a hospital-wide problem that results from government and hospital strategic decision making.

This thesis is the first system dynamics mapping study to characterize core feedback loops found in publicly funded hospitals and is the first system dynamics simulation study to quantify the impact of increased weekend discharges on ED and inpatient bed requirements. Finally, this thesis introduces daily discharge rate as an index of efficiency, responsive to operational change.
CHAPTER 2
UNDERSTANDING HOSPITAL AND EMERGENCY DEPARTMENT CONGESTION: AN EXAMINATION OF INPATIENT ADMISSION TRENDS AND BED RESOURCES

ABSTRACT

Objective: Patients in the emergency department (ED) who have been admitted to hospital (inpatient “boarders”) are associated with ED overcrowding. They are also a symptom of a hospital-wide imbalance between demand and supply of resources. We analyzed the trends of inpatient admissions, ED boarding volumes, lengths of stay and bed resources of 3 major admitting services at our teaching institution.

Methods: We used hospital databases from Jan. 1, 2004 to Dec. 31, 2007, to analyze ED visits that resulted in admission to hospital.

Results: During the study period, 21 986 ED patients were admitted to hospital. The percentage of cancer-related admissions to the oncology decreased from 48% in 2004 to 24% in 2007, while those admitted to General Internal Medicine (GIM) increased nearly two-fold, from 28% in 2004 to 54% in 2007. In addition, GIM admitted ~10% more myocardial infarction and heart failure admissions than Cardiology. GIM constituted the majority of ED boarders and had a median boarding LOS of ~15 hours. Inpatient beds on Oncology and Cardiology services remained static.

**Conclusion:** Without bed capacity to admit more patients, our specialty services relied on GIM to serve as a safety net. At the same time, GIM was cited as a main source of ED congestion as their patients occupied more ED beds for longer periods of time than any other admitting service. The data presented in this study has helped effect positive change within our institution. Other hospitals running at, or near, capacity and faced with similar ED congestion may apply the methods used in this study to analyze the cause and nature of their situation.
The purpose of this chapter is to:

1. Suggest reasons why General Internal Medicine (GIM) inpatients became the main source of ED congestion at TGH.

2. Describe the impact of the study on TGH operations.

2.1 INTRODUCTION

Emergency Department (ED) overcrowding and excessive waiting times for ED treatment are persistent problems for hospitals in many countries. Studies typically report the key indicator of ED overcrowding to be the number of admitted patients occupying beds in the ED while they wait for an inpatient bed to become available, otherwise known as inpatient “boarders” (Andrulis et al., 1991; Richards et al., 2000; Schull et al., 2002; Fatovich et al., 2005; Canadian Institute for Health Information, 2007; Ospina et al., 2007). It is also widely acknowledged that for most hospitals, inpatient boarding is a symptom of an underlying hospital-wide problem: an imbalance between the demand and supply of hospital resources (Forster, 2005; Asplin and Magid, 2007). Accordingly, studies have focused on inpatient supply-related issues, including staffing levels, bed capacity and bed use by patients who no longer require acute care (McClaran et al., 1991; DeCoster et al., 1997; Schneider et al., 2001). In terms of emergent inpatient demand, investigations have focused on predictors of admission and the role elderly (McCusker and Verdon, 2006; Salvi et al., 2007; McDonald et al., 2008; Roberts et al., 2008; Woods et al., 2008). There is general consensus that the most significant contributing factor to ED congestion is inpatient boarders, thus solutions to reduce volumes of boarders and time spent boarding are likely to have the greatest impact on the
ED congestion crisis (Canadian Association of Emergency Physicians, 2001; Olshaker and Rathlev, 2006; Khare et al., 2009).

In recent years at our centre, it has been common for more than half of our ED stretchers to be occupied by inpatient boarders. There was broad agreement between clinicians and hospital management that this posed a threat to patient safety, quality of care, and patient and staff satisfaction. We undertook this study to characterize the ED boarding population at our institution and to understand reasons for the increasing volume of inpatient boarders. We hypothesized that in terms of inpatient boarding volumes and boarding lengths of stay (LOS), one admitting service, General Internal Medicine (GIM), was the main cause of ED congestion at our institution. We further hypothesized that changes in emergent admitting patterns of specialty services, in response to an imbalance of supply and demand for bed resources, influenced GIM admission volumes. We evaluated these hypotheses by examining 1) inpatient admission volumes via the ED, 2) inpatient boarding volumes and LOS, 3) the service of admission and 4) inpatient bed resources.
2.2 METHODS

Study Design

This was a retrospective review of consecutive ED visits that resulted in inpatient admission at Toronto General Hospital (TGH), over a four-year period from January 1, 2004 to December 31, 2007. The University Health Network Research Ethics Board approved this study.

Setting

This study was conducted at TGH, one of three hospitals of the University Health Network (UHN), a research and teaching institute located in downtown Toronto, Ontario. The UHN is also composed of Toronto Western Hospital (TWH), and Princess Margaret Hospital (PMH). Each hospital has unique specialties of care: TGH specializes in heart disease and transplantation; TWH specializes in neuroscience and musculoskeletal science; and PMH is a comprehensive cancer treatment and research center. While TGH and TWH each have their own ED, PMH does not, and its patients are referred to TGH ED (adjacent to PMH) for emergent care.

Selection of Participants

We analyzed data for 21986 consecutive ED visits at TGH that resulted in admission to hospital. This study focused on TGH ED inpatient admissions to GIM and the major specialty programs of cardiac (Cardiology and Cardiovascular Surgery) and cancer care (Oncology) at TGH and PMH, respectively. The TGH ED was chosen for
analyses, as it is the primary emergent admitting site for all specialty programs within TGH and PMH.

Data Collection and Methods of Measurement

We obtained patient-level data from UHN’s primary patient care system Electronic Patient Record (EPR) for ED visits and the administrative information system WinRecs (Med2020 Health Care Software Inc.) for discharged inpatients. The EPR contains information pertaining to socio-demographics, the date and time of patient admission to hospital, the date and time of discharge, the length of stay (defined as the interval from inpatient admission to discharge), diagnosis and patient disposition. In addition, we obtained the number of beds staffed and midnight bed occupancy levels from the financial information system SmartStream (SmartStream Technologies Ltd.). We linked patient records from EPR and WinRecs databases using unique patient and visit identifiers.

Outcome Measures and Primary Data Analyses

Demographic and Visit Characteristics

We examined demographic and visit characteristics of patients admitted to the three services of interest. We included age, sex, LOS and whether an encounter was classified as a “repeat” admission (i.e., the associated unique patient identifier accompanying the encounter was found to be associated with other admissions to the same inpatient service in the calendar year of study).
Inpatient admissions via the ED, boarding volumes and time spent boarding

For each calendar year, we report the total number of ED visits, the total number (and proportion of ED visits) resulting in admission to hospital and the total number (and proportion of inpatient admissions) admitted to the three services of interest.

Ideally, following the decision to admit, inpatients are transferred out of the ED to a ward bed of the service involved. The reality for most visits at our institution is that inpatients board in the ED waiting for a ward bed to become available. To investigate the extent of boarding, we analyzed boarding volumes (measured at midnight) and boarding LOS. We defined boarding volume as the number of inpatients occupying ED beds at midnight. The unit of analysis for boarding volume was one calendar day. We defined boarding LOS as the interval from the time of the decision to admit to the time the patient was transferred out of ED (including transfers to ward beds and ED discharges or deaths).

Shifts in service of inpatient admission

We hypothesized that changes in admitting patterns to cardiac and cancer services would impact GIM admission volumes. To investigate secular changes in the service of inpatient admission, we performed an analysis on ED admissions for cardiac- and cancer-related conditions using the International Classification of Diseases, 10th revision. Applicable cardiac- and cancer-related case-mix group (CMG) codes and descriptions are listed in the legend of Table 2.3.

In addition to investigating cardiac- and cancer-related visits, we further compared admission rates for patients who had received previous care at PMH
(specializing in cancer care) and patients diagnosed with acute myocardial infarction (AMI) or congestive heart failure (CHF).

**Inpatient bed resources**

We also hypothesized that changes in inpatient bed resources would impact GIM inpatient boarding volumes and boarding LOS. We examined the number of beds staffed and midnight bed occupancy levels on the GIM, Oncology (PMH), Cardiology and Cardiovascular Surgery inpatient units.

**Statistical Analyses**

Median and interquartile ranges are reported for continuous variables and proportions are reported for categorical variables. To determine whether significant differences existed across the 4-year study period, we used Kruskal-Wallis one-way analysis of variance by ranks for continuous variables, and $\chi^2$ analysis for proportions. We performed analyses using SPSS (SPSS Inc.) and we deemed an $\alpha$ level of $<$0.05 statistically significant.
2.3 RESULTS

Demographic and Visit Characteristics

We first examined demographic and visit characteristics of GIM, Oncology, and Cardiology and Cardiovascular Surgery admissions from 2004 to 2007 (Table 2.1). During this period, demographics of the three services (i.e., percentage female and median age) remained stable with the most elderly patient admissions occurring in GIM, followed by Cardiology and Cardiovascular Surgery and finally Oncology. Median LOS also remained unchanged for each service, with GIM admissions having the shortest LOS, followed closely by Cardiology and Cardiovascular Surgery, and finally Oncology admissions, which had nearly twice the LOS of GIM. The proportion of repeat admissions for Oncology and Cardiology and Cardiovascular Surgery remained stable at 16.0% and 24.8%, respectively, during the entire study period. In contrast, during the study period there were significant increases in the number of GIM repeat admissions (21.9% in 2004 and 30.0% in 2007).

Inpatient admissions via the ED, boarding volumes and time spent boarding

Table 2.2 summarizes ED visits, inpatient admissions via the ED, and inpatient admissions to GIM, Oncology, and Cardiology and Cardiovascular Surgery. During the study period, there were a total of 112,268 consecutive ED visits at TGH, of which 21,986 resulted in admission hospital. The proportion of inpatient admissions to GIM, Oncology, and Cardiology and Cardiovascular Surgery grew, declined, and remained stable, respectively across the study period. The proportion of ED visits admitted to GIM increased 7.6% in 2007 compared with 2004, whereas those admitted to Oncology decreased 2.2%.
Table 2.1. Emergency department visits admitted to General Internal Medicine, Oncology, and Cardiology and Cardiovascular Surgery inpatient services at Toronto General Hospital, from 2004 to 2007

<table>
<thead>
<tr>
<th>Year</th>
<th>Visit Characteristics</th>
<th>2004</th>
<th>2005</th>
<th>2006</th>
<th>2007</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>General Internal Medicine inpatient admissions, no.</td>
<td>2103</td>
<td>2309</td>
<td>2727</td>
<td>3120</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Age, yr, median (IQR)</td>
<td>69 (54-80)</td>
<td>70 (55-80)</td>
<td>69 (55-80)</td>
<td>69 (54-80)</td>
<td>.39</td>
</tr>
<tr>
<td></td>
<td>Female, no. (%)</td>
<td>970 (46.1)</td>
<td>1117 (48.4)</td>
<td>1307 (47.9)</td>
<td>1435 (46.0)</td>
<td>.49</td>
</tr>
<tr>
<td></td>
<td>Length of stay, days, median (IQR)</td>
<td>5.4 (2.7-10.2)</td>
<td>5.1 (2.7-9.9)</td>
<td>5.2 (2.6-9.6)</td>
<td>4.8 (2.5-9.5)</td>
<td>.07</td>
</tr>
<tr>
<td></td>
<td>Repeat admission*, no. (%)</td>
<td>461 (21.9)</td>
<td>556 (24.1)</td>
<td>771 (28.3)</td>
<td>937 (30.0)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td></td>
<td>Oncology, inpatient admissions, no.</td>
<td>272</td>
<td>226</td>
<td>211</td>
<td>204</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Age, yr, median (IQR)</td>
<td>58 (48-69)</td>
<td>60 (50-68)</td>
<td>60 (51-69)</td>
<td>59 (48-67)</td>
<td>.66</td>
</tr>
<tr>
<td></td>
<td>Female, no. (%)</td>
<td>127 (46.7)</td>
<td>128 (56.6)</td>
<td>108 (51.2)</td>
<td>104 (51.0)</td>
<td>.50</td>
</tr>
<tr>
<td></td>
<td>Length of stay, days, median (IQR)</td>
<td>12.3 (6.5-23.6)</td>
<td>14.3 (7.1-25.5)</td>
<td>11.6 (6.3-22.7)</td>
<td>14.7 (7.5-26.1)</td>
<td>.24</td>
</tr>
<tr>
<td></td>
<td>Repeat admission*, no. (%)</td>
<td>47 (17.3)</td>
<td>35 (15.5)</td>
<td>28 (13.3)</td>
<td>36 (17.6)</td>
<td>.65</td>
</tr>
<tr>
<td></td>
<td>Cardiology and Cardiovascular Surgery, inpatient admissions, no.</td>
<td>576</td>
<td>582</td>
<td>616</td>
<td>698</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Age, yr, median (IQR)</td>
<td>63 (51-74)</td>
<td>63 (51-74)</td>
<td>64 (53-75)</td>
<td>64 (53-74)</td>
<td>.43</td>
</tr>
<tr>
<td></td>
<td>Female, no. (%)</td>
<td>191 (33.2)</td>
<td>182 (31.3)</td>
<td>201 (32.6)</td>
<td>231 (33.1)</td>
<td>.94</td>
</tr>
<tr>
<td></td>
<td>Length of stay, days, median (IQR)</td>
<td>5.7 (2.9-10.9)</td>
<td>5.9 (3.0-11.3)</td>
<td>5.7 (2.6-11.1)</td>
<td>5.0 (2.6-10.7)</td>
<td>.23</td>
</tr>
<tr>
<td></td>
<td>Repeat admission*, no. (%)</td>
<td>133 (23.1)</td>
<td>158 (27.1)</td>
<td>143 (23.2)</td>
<td>178 (25.5)</td>
<td>.43</td>
</tr>
</tbody>
</table>

*to the same inpatient service, via the Emergency department, within calendar year of study
IQR: Interquartile Range

Table 2.2. Emergency department visit volumes at Toronto General Hospital, from 2004 to 2007

<table>
<thead>
<tr>
<th>Year</th>
<th>Emergency Department Volumes</th>
<th>2004</th>
<th>2005</th>
<th>2006</th>
<th>2007</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Emergency Department Visits</td>
<td>25729</td>
<td>26950</td>
<td>29233</td>
<td>30356</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total Inpatient Admissions*</td>
<td>5003 (19.5)</td>
<td>5046 (18.8)</td>
<td>5641 (19.3)</td>
<td>6296 (20.8)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td></td>
<td>General Internal Medicine #</td>
<td>2103 (42.0)</td>
<td>2309 (45.8)</td>
<td>2727 (48.3)</td>
<td>3120 (49.6)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td></td>
<td>Oncology#</td>
<td>272 (5.4)</td>
<td>226 (4.5)</td>
<td>211 (3.7)</td>
<td>204 (3.2)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td></td>
<td>Cardiology and Cardiovascular Surgery#</td>
<td>576 (11.5)</td>
<td>582 (11.5)</td>
<td>616 (10.9)</td>
<td>698 (11.1)</td>
<td>.71</td>
</tr>
</tbody>
</table>

*% of Emergency Department Visits
#% of Inpatient Admissions
Figure 2.1 presents mean ED inpatient boarding volumes measured at midnight for total inpatient admissions, the three services of interest, and all remaining inpatient services. Overall, the fluctuating pattern of total admitting services’ boarders is primarily driven by GIM boarders. In contrast, Oncology and Cardiology and Cardiovascular Surgery boarders account for about 10% of total inpatient boarders. Figure 2.1 also indicates the period when TGH experienced inpatient bed reductions and when a “bed-spacing” policy was put into effect (at our institution, inpatient services are allocated a certain number of physical beds; instituting the bed-spacing policy allowed inpatients to be transferred or “bed-spaced” to empty beds in other services). Figure 2.1 clearly illustrates that the period of inpatient bed reductions resulted in a significant increase in ED boarders. The effect of the bed-spacing policy (intended to relieve ED congestion) is less apparent. In addition to boarding volumes, we analyzed boarding LOS for GIM, Oncology, and Cardiology and Cardiovascular Surgery (Figure 2.2). The median boarding LOS for GIM inpatients was 12.3 hours in 2004, 16.5 hours in 2005, 14.9 hours in 2006, and 14.0 hours in 2007. Overall, GIM boarding LOS was nearly double that of either Oncology or Cardiology and Cardiovascular Surgery.
Figure 2.1: Mean Emergency department (ED) beds occupied at midnight by inpatients at Toronto General Hospital, from 2004 to 2007. Also indicated is the time period (Dec 04 - May 05) when there were reductions or “bed cuts” in the number of General Internal Medicine (GIM) and Cardiovascular (CV) Surgery inpatient staffed beds, and the time at which a bed-spacing policy was put into effect (May 06 onwards), which allowed inpatients to be transferred or “bed-spaced” to empty beds in other services.
Figure 2.2: Box plot showing median boarding length of stay of Cardiology and Cardiovascular (CV) Surgery, Oncology, and General Internal Medicine (GIM) inpatient admissions at Toronto General Hospital, from 2004 to 2007. Boarding length of stay is defined as the interval from Emergency Department (ED) inpatient admission decision to transfer out of the ED. Boxes show interquartile ranges, □ represent mean value, and I bars represent highest and lowest values not considered as outliers.
Shifts in service of inpatient admission

It is evident that the proportion of inpatient visits admitted to GIM increased during the study period. To further investigate the shift to greater GIM admissions, we performed an analysis that was confined to inpatient admissions discharged with CMGs of cancer- or cardiac-related conditions (Tables 2.3a, b). Table 2.3a reveals that each year, cancer-related visits were proportionately less likely to be admitted to Oncology and more likely admitted to GIM ($P < 0.001$). In fact, the proportion of cancer-related visits resulting in admission to Oncology decreased 16.8% in 2007 when compared with 2004, whereas the proportion admitted to GIM increased 21.1%. We further limited the analysis to patients who had already received care at PMH, our cancer care hospital. In this way, we ensured that analyses were restricted to ED visits resulting in admission with already diagnosed cancer (as opposed to cancers newly diagnosed after the admission decision). In this analysis, we found even more pronounced shifts away from Oncology and toward GIM.

For cardiac-related conditions, we found no significant secular trends in the service under which patients were admitted. Cardiology and Cardiovascular Surgery, and GIM admitted consistently about 36% and 55% of patients with cardiac-related conditions, respectively. However, when the analysis was further restricted to visits with CMGs of either AMI or CHF, GIM admitted approximately 10% more AMI or CHF patients in 2007 than in 2004 ($P = 0.07$).
Table 2.3a. Admitting service of Emergency department inpatient admission visits with cancer-related CMGs* at Toronto General Hospital, from 2004 to 2007

<table>
<thead>
<tr>
<th>Admitting Service</th>
<th>2004</th>
<th>2005</th>
<th>2006</th>
<th>2007</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oncology</td>
<td>153 (36.5)</td>
<td>141 (33.4)</td>
<td>109 (26.2)</td>
<td>75 (19.7)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>General Internal Medicine</td>
<td>153 (36.5)</td>
<td>179 (42.4)</td>
<td>216 (51.9)</td>
<td>219 (57.6)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Other Inpatient Service</td>
<td>113 (27.0)</td>
<td>102 (24.2)</td>
<td>91 (21.9)</td>
<td>86 (22.6)</td>
<td>.45</td>
</tr>
<tr>
<td><strong>Modifying Factor: Patient of Princess Margaret Hospital</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Oncology</td>
<td>141 (47.6)</td>
<td>130 (41.9)</td>
<td>97 (32.1)</td>
<td>65 (24.2)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>General Internal Medicine</td>
<td>84 (28.4)</td>
<td>107 (34.5)</td>
<td>142 (47.0)</td>
<td>146 (54.3)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Other Inpatient Service</td>
<td>71 (24.0)</td>
<td>73 (23.5)</td>
<td>63 (20.9)</td>
<td>58 (21.6)</td>
<td>.82</td>
</tr>
</tbody>
</table>

Table 2.3b. Admitting service of Emergency Department inpatient admission visits with heart-related CMGs# at Toronto General Hospital, from 2004 to 2007

<table>
<thead>
<tr>
<th>Admitting Service</th>
<th>2004</th>
<th>2005</th>
<th>2006</th>
<th>2007</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cardiology and Cardiovascular Surgery</td>
<td>277 (37.5)</td>
<td>274 (37.3)</td>
<td>278 (35.5)</td>
<td>327 (35.8)</td>
<td>.88</td>
</tr>
<tr>
<td>General Internal Medicine</td>
<td>397 (53.7)</td>
<td>401 (54.6)</td>
<td>441 (56.3)</td>
<td>504 (55.1)</td>
<td>.92</td>
</tr>
<tr>
<td>Other</td>
<td>65 (8.8)</td>
<td>60 (8.2)</td>
<td>64 (8.2)</td>
<td>83 (9.1)</td>
<td>.89</td>
</tr>
<tr>
<td><strong>Isolation for CMG of Acute Myocardial Infarction or Congestive Heart Failure</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cardiology and Cardiovascular Surgery</td>
<td>139 (42.9)</td>
<td>136 (50.2)</td>
<td>129 (38.1)</td>
<td>109 (36.0)</td>
<td>.04</td>
</tr>
<tr>
<td>General Internal Medicine</td>
<td>147 (45.4)</td>
<td>112 (41.3)</td>
<td>177 (52.2)</td>
<td>166 (54.8)</td>
<td>.07</td>
</tr>
<tr>
<td>Other Inpatient Service</td>
<td>38 (11.7)</td>
<td>23 (8.5)</td>
<td>33 (9.7)</td>
<td>28 (9.2)</td>
<td>.62</td>
</tr>
</tbody>
</table>

AMI = acute myocardial infarction; CHF = congestive heart failure; CMG = case-mix group; ENT = ear, nose and throat; LOS = length of stay; MNRH = may not require hospitalization; PMH = Princess Margaret Hospital.

* Includes CMGs: Neoplasm Of Nervous System (10), ENT Malignancy (100), Respiratory Neoplasms (138), Digestive System Malignancy (279), Hepatobiliary/Pancreatic Malignancy (284), Pancreatic Cancer/Other Hepatobiliary System Malignancy (324), Musculoskeletal Malignant Neoplasm (357), Musculoskeletal Biopsy for Malignancy (361), Secondary Neoplasm/Pathologic Fract (391), Major Gynecological Procedure Ovarian/Adnexal Malignancy (401), Malignant Breast Disorders (443), Urinary Neoplasms (522), Other Musculoskeletal Malignancy (577), Radio-Implant For Malignancy (592), Bone Marrow Transplant (700), Major Leukemia/Lymphoma Procedure (725), Acute Leukemia No Major Procedure (726), Lymphoma/Chr Leukemia With Other Proc (728), Lymphoma & Chronic Leukemia (730), Major Ill-Defined Neoplasm Procedure (733), Ill-Defined Neoplasm With Other Procedure (734), Radiation Therapy (735), Chemotherapy (736), Other Poorly Differentiated Neoplastic Diagnosis (737), Lymphoma With HIV (865).

#Includes CMGs: AMI, Angina, Catheter With Shock/Pulmonary Embolism (200), AMI With Cardiac Catheter With CHF (201), AMI With Cardiac Catheter With Ventricular Tachycardia (202), AMI With Cardiac Catheter With Angina (203), AMI With Cardiac Catheter No Specific Condition (204), AMI No Cardiac Catheter With CHF (205), AMI No Cardiac Catheter With Ventricular Tachycardia (206), AMI No Cardiac Catheter With Angina (207), AMI No Cardiac Catheter No Specific Condition (208), Other/Miscellaneous Cardiac Disorder (209), Unstable Angina With Catheter With Specific Condition (210), Unstable Angina With Catheter No Specific Condition (211), Unstable Angina No Catheter With Specific Condition (212), Unstable Angina No Catheter/Specific Condition (213), Cardiac Catheter With CHF (215), Cardiac Catheter With Ventricular Tachycardia (216), Cardiac Catheter With Unstable Angina (217), Cardiac Catheter No Condition Or Los <4 (218), Endocarditis (219), Pulmonary Embolism (220), Heart Failure (222), Hypertensive Heart Disease (225), Other Circulatory Diagnoses (226), Atherosclerosis (MNRH) (229), Acquired Valve Disorder (MNRH) (232), Hypertension (MNRH) (233), Congenital Cardiac Disorder (MNRH) (234), Angina Pectoris (235), Arrhythmia (237), Syncope And Collapse (240), Chest Pain (242).
Inpatient bed resources

We also analyzed bed staffing levels and midnight bed occupancy levels on GIM, Oncology (at PMH), Cardiology and Cardiovascular Surgery inpatient units (Table 2.4). Oncology staffed beds significantly decreased from about 116 in 2004 to about 113 in 2005-2007, while midnight bed occupancy remained stable at about 93% over the four years. Neither staffed beds nor bed occupancy levels changed significantly for Cardiology (26 beds at ~93% occupancy during the study period). Cardiovascular Surgery staffed beds significantly decreased in 2005 compared with 2004 (a reduction of ~6 beds), but returned to 2004 levels by 2007. Midnight bed occupancy levels were the lowest of the four services analyzed, ranging from 85%-90% occupancy. Similar to Cardiovascular Surgery, GIM staffed beds decreased in 2005 when compared with 2004 (reduction of ~4 beds). By 2007, GIM staffed beds had increased (from ~71 in 2006 to ~82 in 2007). Overall, GIM midnight bed occupancy consistently increased during the study period, from 94% in 2004 to more than 96% use in 2007, maintaining the highest occupancy levels of the four services analyzed.
Table 2.4. Inpatient staffed beds and midnight bed census at Toronto General Hospital and Princess Margaret Hospital, from 2004 to 2007

<table>
<thead>
<tr>
<th>Admitting Service</th>
<th>Year</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2004</td>
<td>2005</td>
<td>2006</td>
<td>2007</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Oncology</td>
<td>Staffed beds, no., median (IQR)</td>
<td>116.3 (114.5-116.8)</td>
<td>113.1 (111.9-113.3)</td>
<td>113.3 (112.2-113.7)</td>
<td>113.6 (111.9-113.8)</td>
<td>.002</td>
</tr>
<tr>
<td></td>
<td>Bed occupancy, %</td>
<td>92.2</td>
<td>93.6</td>
<td>92.7</td>
<td>92.5</td>
<td>.21</td>
</tr>
<tr>
<td>Cardiology</td>
<td>Staffed beds, no., median (IQR)</td>
<td>26.0 (25.5-26.0)</td>
<td>25.8 (25.5-26.0)</td>
<td>26.0 (25.1-26.0)</td>
<td>26.0 (26.0-26.0)</td>
<td>.27</td>
</tr>
<tr>
<td></td>
<td>Bed occupancy, %</td>
<td>91.1</td>
<td>92.6</td>
<td>93.3</td>
<td>94.1</td>
<td>.18</td>
</tr>
<tr>
<td>Cardiovascular Surgery</td>
<td>Staffed beds, no., median (IQR)</td>
<td>52.0 (51.2-52.1)</td>
<td>46.9 (46.0-47.7)</td>
<td>49.5 (46.0-50.9)</td>
<td>51.8 (51.1-52.0)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td></td>
<td>Bed occupancy, %</td>
<td>85.3</td>
<td>86.0</td>
<td>89.4</td>
<td>88.0</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>General Internal Medicine</td>
<td>Staffed beds, no., median (IQR)</td>
<td>70.0 (69.8-70.0)</td>
<td>66.2 (59.4-66.5)</td>
<td>70.7 (69.7-71.1)</td>
<td>82.7 (80.7-84.8)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td></td>
<td>Bed occupancy, %</td>
<td>93.6</td>
<td>94.0</td>
<td>95.8</td>
<td>96.4</td>
<td>.001</td>
</tr>
</tbody>
</table>

IQR: Interquartile Range
2.4 DISCUSSION

We set out to analyze inpatient admissions via the ED at our organization. Our goal was to provide insightful data to hospital management on the nature of our ED congestion crisis. Specifically, we wanted to understand where the increasing volume of inpatients who were boarded in the ED was coming from. Our results indicate that the shifting admission pattern from specialty to GIM services created the appearance of a GIM problem, when in reality an institutional problem existed. We found that in each progressive year, the GIM service admitted a greater proportion of total inpatients and their patients occupied more ED beds for longer periods than any other inpatient admitting service. Allowing patients to be transferred or “bed-spaced” to empty ward beds in other inpatient services did not significantly change the number of ED boarders. In our analyses of inpatient volumes, we observed significant increases in total inpatient admissions (Table 2.2) and bed occupancies (Table 2.4), suggesting that even with a bed-spacing policy in place, movement of inpatients out of the ED was severely limited because of the lack of beds. This may be indicative of a larger hospital-wide capacity issue beyond the ED, or reflect a flaw in the design or implementation of the policy (Abu-Laban, 2006). A dedicated unit for immediate transfer of admitted medical patients has been previously found to reduce ED boarding volumes (Moloney et al., 2006).

There is evidence to suggest that the shift away from admission to specialty services and toward GIM may be for reasons other than clinical. We found reductions in the proportion of admissions to Cardiology and Cardiovascular Surgery for myocardial infarction and congestive heart failure, while the proportions admitted to GIM increased. Even more striking was the two-fold proportionate reduction in admissions to Oncology
for cancer-related diagnoses even when these visits had received previous care at PMH. General Internal Medicine on the other hand, experienced a nearly two-fold proportionate increase in admission of these cancer-related visits. As demand continues to increase for specialty services, such as ambulatory cancer care (Cancer Care Ontario, 2008), monitoring the ambulatory-emergent-inpatient feedback relationships will be essential when making decisions about hospital resource allocation (Schull et al., 2001). We also observed that the proportion of GIM admissions that were repeat visits grew significantly during the study period. This may reflect overly aggressive discharge planning, lack of outpatient care coordination or deficits in the quality of care. Alternatively, this may be due to a changing patient population, for example, an increase in late-stage oncology patients with predictable subsequent admissions requiring inpatient care.

Finally, we observed that the number of staffed beds on Cardiology and Oncology remained relatively unchanged during the study period. When considered with our findings regarding admission diagnoses, this suggests that bed resources influenced admission decisions. In lieu of increased bed capacity, it appears that specialty services strictly regulate their emergent inpatient admissions. A study by Kroneman and Siegers (Kroneman and Siegers, 2004) that investigated the manner in which bed reductions affect the use of remaining beds, supports this conclusion. The results of this study indicated that the number of admissions and the share of beds kept empty for emergency cases were reduced when hospital beds were cut (Kroneman and Siegers, 2004). Without the capacity to admit more patients, our specialty services relied on GIM to serve as a safety net. We also found that inpatient bed reductions increased the number of inpatient boarders in the ED. Reports have shown that the lack of inpatient beds and high hospital
occupancy are important determinants of inpatient boarders in the ED (Forster et al., 2003; Hwang, 2006; Hoot and Aronsky, 2008).

Our investigation highlights the need for a comprehensive approach to improving ED congestion. In particular, it illustrates how ED congestion is exacerbated when hospitals expand their specialty services and procedures, while allowing these services to “opt out” of the more complex, long-term and recurring inpatient care, especially if such patients are redirected to an already busy GIM inpatient service. The data presented in this study has had a positive effect on senior management within our institution. Clinicians and medical directors have worked together to realign patient volumes and redistribute care across the organization. This work has included revisions to the escalation policy and ED consultation guidelines that provide guidance on what conditions are appropriate for admission for each inpatient service. Significant progress has been made at our institution in reducing boarding volumes and LOS since implementation of the reformed policies in September 2008. Figure 2.3 presents average ED inpatient boarding volumes and median boarding LOS for GIM (Panel A) and total inpatient admissions (Panel B) for calendar years 2007 and 2008. For 2007, the typical seasonal pattern of high boarding volumes during the fall, winter and spring months followed by a lull in the summer months is illustrated. A similar pattern can be seen at the beginning of 2008; however, the reduction of inpatient boarders during the summer months is sustained through the fall and early winter, suggesting that the reforms that took place in September 2008 were helpful in improving the number of inpatient boarders and time spent boarding in our ED.
Figure 2.3: Mean Emergency Department (ED) beds occupied at midnight by inpatients (line) and median boarding length of stay (bars) for GIM (A) and Total Admitting Services (B) at Toronto General Hospital for 2007 and 2008. Boarding length of stay is defined as the interval from Emergency Department (ED) inpatient admission to transfer out of the ED. Arrow denotes when ED Admitting and Escalation Policy reforms took effect.
Our study has several limitations. First, we chose to study Cardiology and Cardiovascular Surgery, and Oncology admitting services primarily because they are the premier specializations of care at TGH and PMH, respectively. However, we readily acknowledge that there are diagnoses in which expertise may overlap between the two services and GIM. Second, we analyzed CMGs instead of ED presenting complaint, as we felt it would be more informative for a retrospective analysis of the most appropriate service for admission. However, the list of CMGs considered as cancer- and cardiac-related is not exhaustive, nor has it been validated. As a result, there is potential that we may have underestimated the total number of ED admissions attributable to cancer and cardiac conditions. In spite of this, our analysis still reveals important data on an apparent shift in service of inpatient admission away from Cardiology and Cardiovascular Surgery and Oncology, and toward GIM. Finally, this study took place in one large teaching institution, and as a consequence, may be less generalizable to other community hospitals.

In conclusion, our study found that during a four-year period GIM increasingly became the service to which they were admitted, even though historically some had been cared for by Cardiology and Oncology specialty services. General Internal Medicine patients also occupied more ED beds for longer periods than they did for any other service. Moreover, of the three services analyzed, GIM maintained the highest bed occupancy levels and had the shortest LOS. The data presented in this study were of interest to senior management within our institution and contributed to the progress achieved in reducing the number of inpatients boarding in the ED. Further research is required to better understand how organizations should balance supply with demand in
order to provide optimal care to their patient populations. Other hospitals running at or near capacity and faced with similar ED congestion may apply the methods we used in this study to analyze the cause or nature of their situation.
CHAPTER 3
HOW MUCH DO OPERATIONAL PROCESSES AFFECT HOSPITAL
INPATIENT DISCHARGE RATES?

ABSTRACT

**Background:** The objective of this study is to determine the effect of day of the week, holiday, team admission and rotation schedules, individual attending physicians, and their length of coverage on daily team discharge rates.

**Methods:** We conducted a retrospective analysis of the General Internal Medicine (GIM) inpatient service at our institution for years 2005 and 2006, which included 5088 patients under GIM care.

**Results:** Weekend discharge rate was more than 50% lower compared to reference rates while Friday rates were 24% higher. Holiday Monday discharge rates were 65% lower than regular Mondays, with an increase in pre-holiday discharge rates. Teams that were on-call or that were on call the next day had 15% higher discharge rates compared to reference while teams that were post-call had 20% lower rates. Individual attending physicians and length of attending coverage contributed small variations in discharge rates. Resident scheduling was not a significant predictor of discharge rates.

**Conclusions:** Day of the week and holidays followed by team organization and scheduling are significant predictors of daily variation in discharge rates. Introducing greater holiday and weekend capacity as well as reorganizing internal processes such as admitting and attending schedules may potentially optimize discharge rates.

The purpose of this chapter is to:

1. Explore the effect of day of the week, holiday, team admission and rotation schedules, individual attending physicians, and their length of coverage on daily team discharge rates

2. Determine which of these operational factors are significant predictors of daily variation in discharge rates

3.1 INTRODUCTION

Improving patient flow in acute care hospitals is an important issue in hospital management and research. Improved patient flow can decrease wait times for care, ease Emergency Department (ED) congestion, and increase the effective capacities of the ICU and inpatient units (Forster et al., 2003; Proudlove et al., 2003; Hoot and Aronsky, 2008; Van Houdenhoven et al., 2008). One way to improve patient flow is to remove variation in processes along the care pathway that can block or delay flow (Institute for Healthcare Improvement, 2003). One process in particular – patient discharge – has received critical attention because variation and delays in this process create “bottlenecks” that ultimately delay most care pathways, especially new admissions from the Emergency Department (Asplin and Magid, 2007; Canadian Institute for Health Information, 2007).

While the decision to discharge an individual patient from hospital should predominately be a clinical decision, there may be non-clinical factors that influence decision-making. These may include patient and family preferences (Bryan et al., 2006), physician practice preferences (Shepperd et al., 2004), internal hospital inefficiencies
(Baumann et al., 2007), post-acute care bed capacity (Glasby et al., 2006), and healthcare financing arrangements.

The impact of non-clinical hospital discharge delays on costs, quality, and appropriateness of care has garnered international attention. In the United States where hospitals are reimbursed prospectively, one study found that ~7% of hospital days were judged unnecessary and were due to difficulty finding a bed in a skilled nursing facility (Carey et al., 2005). In the UK, where transfer from acute inpatient hospital care to ongoing health and social care is subject to means-testing and user charges, the Community Care Act 2003 was introduced that allowed hospital trusts to charge social service departments (providing ongoing health and social care in the community) for hospital beds unnecessarily ‘blocked’ by people awaiting social services (McCoy et al., 2007). In Canada, universal health insurance covers medically necessary in- and outpatient hospital services as well as extended health services (certain aspects of long-term residential care and the health aspects of home care and ambulatory care services)(Health Canada, 2008). Hospitals receive block funding and chronically face budget deficits(Blake and Carter, 2003). There is increasing accountability on hospitals to meet benchmarks on wait times in the ED, for diagnostic imaging, and for selected elective surgeries, all while maintaining a balanced budget (Canadian Institute for Health Information, 2006). Thus, patients occupying acute care beds who are awaiting transfer to a community facility represent a significant challenge in timely acute care hospital discharge (Ontario Hospital Association, 2006).

While efforts have been made to better coordinate care between acute and post-acute sectors (Henwood, 2006), understanding factors within an acute care hospital’s
control should be a top priority, as reducing them may improve efficiency. Several studies have focused on internal hospital operational factors including the day of the week of admission in terms of internal resource availability (Earnest et al., 2006), team organization and workload, and clinician behaviour (Laing et al., 2004) to understand how they contribute to variations in discharge. In these studies, the primary outcome measure was length of stay. An alternative metric to measure the impact of hospital operational factors on the discharge process is daily discharge rate (Chow and Szeto, 2005). Daily discharge rate incorporates day of the week explicitly and may highlight other operational factors that exhibit temporal patterns including staffing and scheduling.

The objective of this study was to determine the effect that the following operational factors had on discharge rates: day of the week, holiday status, team admission schedule, resident scheduling, individual attending physicians, and the length of attending physician coverage. Our primary outcome measure was mean daily team discharge rate, expressed as the number of team discharges divided by team census on a particular day.
3.2 METHODS

We conducted a retrospective analysis of the General Internal Medicine (GIM) inpatient service at Toronto General Hospital for two consecutive years, 2005 and 2006. We wanted to determine the effect of day of the week, holiday status, team admission schedule, resident scheduling, and attending physician schedule on team discharge rates. University Health Network (UHN) Research Ethics Board approved this study.

Setting

This study was conducted on the GIM inpatient service at the University Health Network’s Toronto General Hospital site, a 400-bed tertiary care centre and teaching hospital located in downtown Toronto, Canada. GIM provides acute, non-surgical health care to a patient population primarily composed of elderly patients with complex, chronic illnesses. GIM receives 98% of its inpatient admissions from the Emergency Department, other sources being transfers from other services (CCU, ICU, surgery, etc.) and other institutions. Of all patients requiring admission from the Emergency Department, GIM receives the largest share (30-50% of all ED admissions).

During the study period, there were four admitting teams. Each team consisted of one attending physician, one resident, and two interns. Each day, the team assigned to be on-call accepted new admissions from 8 AM to 8 AM the following day, at which time they transitioned to post-call status. During weekends, the on-call team was responsible for all admitting duties as well as clinical duties for all GIM admissions. Teams (resident and interns) rotated every two months, while attending physicians normally rotated on a
monthly basis. Attending physician rotations could range from half a month to two consecutive months. Attending physicians were not assigned exclusively to one team.

**Data Collection**

Data was collected from January 15th to December 15th for the two years, 2005 and 2006. We excluded the period December 16th – January 14th from our analyses due to Christmas/New Year holiday disruptions to physician team structures. To simplify analyses, we only selected holidays that occurred on a Monday, thus excluding Easter (Mar 24-29, 2005 and Apr 13-18, 2006) and Canada Day (Jun 30-Jul 4, 2005 and Jun 30-Jul 4, 2006) from analysis. The unit of analysis was a day, defined as the 24hr period from 08:00-08:00. The time period of 08:00-08:00 was chosen because it better reflects the period when decisions are made and work is completed.

Patient-level data was obtained from University Health Network’s primary patient care system Electronic Patient Record (EPR). EPR contains information pertaining to sociodemographics, diagnosis, length of stay (LOS), patient disposition, attending physician, admission and discharge dates and times. Attending physician schedules, team admission schedules, and resident schedules were obtained from team rosters maintained by the GIM residency program. We included all GIM inpatient admissions that were under the care of GIM services during the study period (i.e. patients whose admission or discharge dates were within the study period and patients admitted before the start of the study period and discharged after the end of the study period).
Outcomes

Our primary study outcome was mean daily team discharge rate, expressed as the number of discharges divided by census for a specific team on a particular day. Daily team discharge rate was chosen as opposed to the overall discharge rate because each team effectively acted as an independent unit and it allowed us to look at variations caused by scheduling. Daily team census was measured at 8 AM. To retain a focus on operational factors that can act as bottlenecks in discharge, we excluded discharges with disposition of either death or left against medical advice from daily discharge rate calculations. These visits were however maintained for daily census calculations.

Predictors

Day of the Week and Holiday Status

We examined if day of the week or a holiday period was a predictor of daily team discharge rates. Holiday Mondays included Victoria Day (May 23, 2005 and May 22, 2006), Civic Holiday (Aug 1, 2005 and Aug 7, 2006), Labour Day (Sep 5, 2005 and Sep 4, 2006), and Thanksgiving Day (Oct 10, 2005 and Oct 9, 2006). A priori, we believed that in anticipation of a Holiday Monday, proactive measures to increase discharge rates would be taken pre-holiday period (either by physician purposeful behaviour or by request of patient and/or patient’s family), or conversely reactive measures would be taken post-holiday period. Fridays, Saturdays, and Sundays immediately preceding a Holiday Monday were defined as pre-holiday days. Tuesdays immediately following a Holiday Monday were defined as post-holiday days. ‘Regular’ weekdays and weekends included all days in the study period except pre-/post-/Holiday Mondays listed above.
Clinical Scheduling

We examined whether the scheduling of team admissions, resident scheduling, or attending physicians was a predictor of daily team discharge rates. According to the team admission schedule, each day, each team was assigned either pre-call, on-call, post-call, post-post-call, or no-call status (team neither pre-call, on-call, post-call nor post-post-call) (Figure 3.1). Each call-status was equally likely to occur during the seven days of the week, with the exception of no-call status, which only occurred on weekends. We anticipated that discharge rates for post-call teams would be significantly decreased since post-call teams were relieved of hospital duties at 12 PM. We hypothesized that there would be an increase in discharge rates for pre-call teams in anticipation of the increased workload of new admissions the following day.

We also examined whether resident scheduling was a predictor of daily team discharge rates. Residents are scheduled for durations of two months. We anticipated that there would be differences in team discharge rates for three distinct periods during the two months: first week, last week, and all remaining weeks. We hypothesized that in the first week of the two month period, teams were newly acquainted with their patients and as a result, would be less likely to discharge them compared to remaining weeks. In contrast, in the last week of the two months, teams were well acquainted with their patients and would be more likely to discharge them compared to other weeks.
**Figure 3.1:** A typical four-week period for one of the admitting teams. Note the other teams would have similar schedules. A team is on-call for a 24-hour period (Monday 8AM to Tuesday 8AM). After working for the 24 hours, the team is now considered post-call, and would leave early after signing over their patients. The next day is considered the post-post-call day. Note that while a team is on-call 1 in 4 days, a strict every fourth day on call is not followed. This results in certain time when teams could be considered both post-post-call and on-call. For the purposes of this analysis, we considered that team on-call.

<table>
<thead>
<tr>
<th></th>
<th>Sunday</th>
<th>Monday</th>
<th>Tuesday</th>
<th>Wednesday</th>
<th>Thursday</th>
<th>Friday</th>
<th>Saturday</th>
</tr>
</thead>
<tbody>
<tr>
<td>Week 1</td>
<td></td>
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<td>Week 2</td>
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<tr>
<td>Week 3</td>
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<tr>
<td>Week 4</td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

Legend:
- Pre-call
- On-call
- Post-call
- Post-post-call
- No-call
Finally, we examined whether individual attending physicians had different daily team discharge rates and whether the length of coverage assigned to an attending affected discharge rates. We anticipated no major difference in aggregate daily discharge rate among the different attending physicians during the course of the study period; however, we hypothesized that there would be differences in discharge rates for physicians attending for shorter periods (i.e. ≤ 15 days) versus longer coverage periods (i.e. ≥30 days). Physicians who are attending for short periods may be less inclined to be actively involved in discharge planning. In addition, physicians nearing their end of their coverage period may be less motivated to discharge patients. To account for the length of attending service and proximity to end of service coverage for each day of the study period, we calculated the numbers of days since the start of team coverage and the numbers of days till the end of team coverage for each of the four attending physicians on service.

**Statistical Analyses**

Preliminary analysis of the data included the calculation of descriptive statistics to summarize GIM patient admission and service characteristics. We reported medians and interquartile ranges for continuous variables and proportions for categorical variables. All regression analyses used a linear mixed random effects model with the number of discharges by a team on a day treated as a Poisson random variable. In all analyses, we accounted for the effects of clustering of the four team outcomes within a day by including a random effect for day. All analyses also included a 6-degree-of-
freedom natural spline fitted to the calendar time variable to account for seasonal fluctuation and correlation between outcomes on adjacent days.

In four separate univariable regressions, we assessed the relationship between discharge rate and each of the predictor variables (type of day, team admission schedule, resident scheduling, and the length of attending physician coverage). We also ran a model with a random effect for the attending physician; this allowed each attending physician to have a discharge rate that is either higher or lower than the average. Finally, we fitted a model with all four predictors and the random effect for attending physician. We report the rate ratios and 95% confidence intervals, compared to a reference group for categorical predictors, and per 30 days for attending physician coverage. We also report the standard deviation between log-rate ratios for individual attending physicians. All statistical analyses were performed using R (version 2.8.0: R Foundation for Statistical Computing, Vienna, Austria); and 2-tailed \( P < .05 \) was considered statistically significant in all analyses.
3.3 RESULTS

Patient and Service Characteristics

During the 648-day study period, there were 5,088 patients under the care of GIM services (Table 3.1). 98% of patients were admitted from the ED, 2% were directly admitted. The median age of patients was 68 years and 48% were women. Patient dispositions following GIM care during the study period included: discharge home (72%), transfer to other facility including other acute care facilities, rehabilitation, long-term care, respite care, complex continuing care (14%), in-hospital death (7%), transfer to another inpatient service within UHN (6%), and lastly left against medical advice (2%). The overall median LOS was 5 days. Measured at 8AM, daily median GIM census was 66 patients. On a daily basis, both the median number of admissions and discharges to and from GIM services was 7 patients. At the team level, median daily census was 16 patients, median number of daily discharges was 1 patient, and median daily team discharge rate was 9% of team census.

Day of the Week and Holiday Status

The day of the week accounted for a significant amount of variation in discharge rates in both unadjusted and adjusted models (Figure 3.2 and Table 3.2). Wednesday was chosen as the reference. For regular weekends, both Saturday and Sunday had significantly lower (by 50% P < .001, and 71% P < .001, respectively) adjusted rates of discharge relative to Wednesday. For regular weekdays, whereas Monday, Tuesday and Thursday had similar adjusted discharge rates relative to Wednesday (8%, 5% and 6% lower, respectively), Friday had significantly higher discharges (by 24%, P < .001) relative to Wednesday.
### Table 3.1: General Internal Medicine Patient and Service Characteristics

<table>
<thead>
<tr>
<th>General Internal Medicine Patient Characteristic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>N = 5088 patients</td>
<td></td>
</tr>
<tr>
<td>Admitted via ED, no. (%)</td>
<td>4994 (98.2)</td>
</tr>
<tr>
<td>Median age, yrs (IQR)</td>
<td>68 (54-80)</td>
</tr>
<tr>
<td>Female sex, no. (%)</td>
<td>2452 (48.2)</td>
</tr>
<tr>
<td>Inpatient Mortality, no. (%)</td>
<td>334 (6.6)</td>
</tr>
<tr>
<td>Left Against Medical Advice, no. (%)</td>
<td>86 (1.7)</td>
</tr>
<tr>
<td>Median length of stay, days (IQR)</td>
<td>5 (3-10)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>General Internal Medicine Service Characteristic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>N = 648 days</td>
<td></td>
</tr>
<tr>
<td>Median census in @ 8AM, patients (IQR)</td>
<td>66 (60-72)</td>
</tr>
<tr>
<td>Median team census @ 8AM, patients (IQR)</td>
<td>16 (13-19)</td>
</tr>
<tr>
<td>Median admissions, patients (IQR)</td>
<td>7 (5-9)</td>
</tr>
<tr>
<td>Median discharges, patients (IQR)</td>
<td>7 (4-9)</td>
</tr>
<tr>
<td>Median team discharges, patients (IQR)</td>
<td>1 (1-3)</td>
</tr>
<tr>
<td>Median daily team discharge rate, % team census (IQR)</td>
<td>9 (4-16)</td>
</tr>
</tbody>
</table>
Figure 3.2: Adjusted discharge ratios and 95% confidence intervals evaluating day of the week and holiday (Hol) periods. Wednesday is reference variable. Each measure reports the change in proportion of team census discharged compared to reference.
Table 3.2. Univariate and Multivariate Analysis of Operational Factors on Team Discharge Rates

<table>
<thead>
<tr>
<th>Variable</th>
<th>Discharge Rate Ratio</th>
<th>95% CI</th>
<th>P value</th>
<th>Discharge Rate Ratio</th>
<th>95% CI</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Day of the Week</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Holiday Monday</td>
<td>0.32</td>
<td>0.20-0.49</td>
<td>&lt;0.001</td>
<td>0.32</td>
<td>0.21-0.51</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Monday</td>
<td>0.90</td>
<td>0.81-1.00</td>
<td>0.05</td>
<td>0.92</td>
<td>0.83-1.02</td>
<td>0.11</td>
</tr>
<tr>
<td>Post-Holiday Tuesday</td>
<td>1.12</td>
<td>0.89-1.43</td>
<td>0.34</td>
<td>1.13</td>
<td>0.89-1.44</td>
<td>0.32</td>
</tr>
<tr>
<td>Tuesday</td>
<td>0.95</td>
<td>0.86-1.05</td>
<td>0.31</td>
<td>0.95</td>
<td>0.86-1.05</td>
<td>0.35</td>
</tr>
<tr>
<td>Wednesday*</td>
<td>1</td>
<td>-</td>
<td>-</td>
<td>1</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Thursday</td>
<td>0.93</td>
<td>0.85-1.03</td>
<td>0.19</td>
<td>0.94</td>
<td>0.85-1.03</td>
<td>0.19</td>
</tr>
<tr>
<td>Pre-Holiday Friday</td>
<td>1.54</td>
<td>1.25-1.89</td>
<td>&lt;0.001</td>
<td>1.57</td>
<td>1.28-1.93</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Friday</td>
<td>1.24</td>
<td>1.13-1.37</td>
<td>&lt;0.001</td>
<td>1.24</td>
<td>1.13-1.37</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Pre-Holiday Saturday</td>
<td>0.62</td>
<td>0.44-0.86</td>
<td>0.004</td>
<td>0.70</td>
<td>0.50-0.98</td>
<td>0.04</td>
</tr>
<tr>
<td>Saturday</td>
<td>0.45</td>
<td>0.39-0.51</td>
<td>&lt;0.001</td>
<td>0.50</td>
<td>0.43-0.57</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Pre-Holiday Sunday</td>
<td>0.36</td>
<td>0.24-0.55</td>
<td>&lt;0.001</td>
<td>0.39</td>
<td>0.26-0.6</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Sunday</td>
<td>0.27</td>
<td>0.23-0.32</td>
<td>&lt;0.001</td>
<td>0.29</td>
<td>0.25-0.34</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td><strong>Attending Physician Coverage</strong></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Days from start of coverage†</td>
<td>1.01</td>
<td>0.93-1.10</td>
<td>0.76</td>
<td>1.10</td>
<td>1.00-1.20</td>
<td>0.04</td>
</tr>
<tr>
<td>Days to end of coverage†</td>
<td>1.02</td>
<td>0.94-1.12</td>
<td>0.58</td>
<td>1.01</td>
<td>0.92-1.11</td>
<td>0.84</td>
</tr>
<tr>
<td><strong>Team Admitting Schedule</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pre-call</td>
<td>1.15</td>
<td>1.06-1.25</td>
<td>0.001</td>
<td>1.17</td>
<td>1.07-1.27</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>On-call</td>
<td>1.06</td>
<td>0.97-1.15</td>
<td>0.21</td>
<td>1.15</td>
<td>1.05-1.25</td>
<td>0.002</td>
</tr>
<tr>
<td>Post-call</td>
<td>0.75</td>
<td>0.69-0.82</td>
<td>&lt;0.001</td>
<td>0.80</td>
<td>0.74-0.87</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>No-call</td>
<td>0.40</td>
<td>0.32-0.49</td>
<td>&lt;0.001</td>
<td>0.73</td>
<td>0.58-0.91</td>
<td>0.005</td>
</tr>
<tr>
<td>Post-post-call†</td>
<td>1</td>
<td>-</td>
<td>-</td>
<td>1</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td><strong>Resident Rotation Schedule</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>First week</td>
<td>0.94</td>
<td>0.81-1.09</td>
<td>0.427</td>
<td>0.98</td>
<td>0.88-1.09</td>
<td>0.651</td>
</tr>
<tr>
<td>Last week</td>
<td>1.08</td>
<td>0.94-1.24</td>
<td>0.298</td>
<td>1.02</td>
<td>0.92-1.13</td>
<td>0.668</td>
</tr>
<tr>
<td>Not first or last week*</td>
<td>1</td>
<td>-</td>
<td>-</td>
<td>1</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td><strong>Random Effect of Attending</strong></td>
<td></td>
<td>SD=0.054</td>
<td>0.04</td>
<td>SD=0.061</td>
<td>-</td>
<td>0.006</td>
</tr>
</tbody>
</table>

* reference variable
† per 30 days
Adjusted rates of discharge on Holiday-Monday were significantly lower than regular Mondays with Holiday-Monday discharge rates being 65% lower than rates on a regular Monday (P < .001). Discharge rates on a pre-holiday Friday were 27% higher than rates on a regular Friday (P = .04). While pre-holiday Saturday and Sunday had rates that were higher than their corresponding regular weekend days, these increases were not statistically significant (Saturday: 40% higher, P = .06; and Sunday: 34% higher, P = .22). In contrast, discharge rates on a post-holiday Tuesday were similar to regular Tuesdays (P = .17).

**Clinical Scheduling**

Following type of day, team admission schedule ranked as the next most important predictor of variation in discharge rates in both unadjusted and adjusted models. Post-post-call teams were chosen as the reference. Relative to post-post call teams, pre-call and on-call teams had significantly higher (by 17% and 15%, respectively) adjusted rates of discharge (P < .001, P = .002, respectively), while post-call and no-call teams had significantly lower (by 20% and 27%, respectively) adjusted rates of discharge (P < .001, P = .005, respectively).

Resident scheduling was not a predictor of discharge rates in either unadjusted or adjusted models. Weeks other than the first or last weeks of resident rotation were chosen as the reference. Adjusted discharge rates during the first and last weeks of resident rotation schedule were similar to middle weeks (P = .65 and P = .67, respectively).
Individual attending physicians and their length of scheduled coverage was a predictor of discharge rates in the adjusted model. There were 28 different attending physicians that covered the 4 teams during the study period. There was a small but significant random effect for the attending physicians in the adjusted model, wherein attending physicians had discharge rates that ranged from 8% below average to 4% above average ($P = .006$). Length of attending physician coverage ranged from a minimum of 14 consecutive days to a maximum of 64 consecutive days. There was a small but significant increase in adjusted rates of daily discharge as the term length (days from start of attending coverage) increased (by 10% per 30 days attending, $P = .04$). Proximity to end of term coverage (days till end of attending coverage) was not a significant predictor of daily discharge rate ($P = .84$).
3.4 DISCUSSION

Main finding of this study

We found that discharge rates within a General Internal Medicine inpatient service were affected by the day of the week, holiday status, team admission schedule, individual attending physicians and their length of attending coverage. Adjusted discharge rate ratios and 95 percent confidence intervals for the majority of predictors were virtually identical to the unadjusted discharge rate ratios, confirming that the effects of the predictors are independent of each other. Weekend discharge rate was significantly lower than weekday discharge rate. More discharges occurred on Fridays than other days, possibly to compensate for reduced weekend discharges. Holiday Monday discharge rates were significantly lower than regular Mondays with increases in pre-holiday discharge rates. More discharges occurred when a team was either pre-call or on-call status, and significantly less discharges occurred for teams on post-call status. Resident scheduling was not a significant predictor of team discharge rates. Individual attending physicians had small but significant variation in team discharge rates, and as the length of attending coverage increased, so did the rate of discharge.

What is already known on this topic

We investigated the effect of weekends and holidays on discharge rates because it has received considerable attention as a source of hospital inefficiency (Weissman and Bendavid, 2004; Redelmeier and Bell, 2007). While discharges and discharge rates should be predominately clinical decision, there is significant variation caused by hospital processes. Understanding these variations may be key to improving efficiency. A study
by Carey et al. to quantify delays in care for general medicine inpatients found that nearly 25% of unnecessary patient-days involved an inability to access medical services on a weekend day (Carey et al., 2005). The data on weekends reported here are consistent with and extend findings from previous studies that have evaluated the effect of weekends on patient flow. It has been previously shown that discharge rates are significantly higher on Fridays and lower over the weekends and that these results are independent of clinical indicators of risk (Varnava et al., 2002). One explanation for this phenomenon is that availability of hospital resources including physicians and hospital staff are decreased on weekends. To avoid the weekend, patients were preferably discharged on Friday. A similar explanation may be used to explain increased pre-holiday discharges relative to their regular counterpart days. Reduced weekend capacity also applies to many community resources and post-acute care institutions making it unfeasible to discharge patients that require home care or transfer to other institutions on weekends. Patient and family preferences may also be relevant in determining the day of week of discharge.

**What this study adds**

Our study introduces daily team discharge rate, expressed as the number of discharges divided by census for a specific team on a particular day. While daily discharge rate explicitly incorporates day of the week trends, there are implicit factors operating at many different levels that influence its value. Likelihood of discharge is affected by the composition of the ultimate discharge destinations of the current patient
census (home versus transfer to another facility). Similarly the proportion of team census considered ‘long-stay’ will also affect daily team discharge rate.

Our study further highlights the importance of considering full utilization of hospital capital designed to operate 7 days a week. Bell and Redelmeier found that even conservative growth in weekend service can achieve an increase in procedure volumes of \( \sim 15\% \) (Bell and Redelmeier, 2005). Our study also showed that team organization and scheduling is a significant predictor of daily team discharge rates. Teams discharged a significantly greater proportion of their patients during pre-call and on-call days and significantly fewer on post-call days. Clinically, pre-call teams have patients that have had at least three days of diagnostic and therapeutic care and therefore would be expected to be more ready for discharge than post-call teams that have a larger proportion of their patient census consisting of new patients with active clinical issues. A plausible non-clinical explanation for increased pre-/on-call discharges is that in anticipation of increased workload/census due to new admissions, teams purposefully discharged more of their patients. While in our admission system, we get a ‘bolus’ of patients on average every four days, other systems have been proposed that have daily admissions, a ‘drip’ admission process. If our traditional ‘bolus’ admitting system in place was replaced with ‘drip’ admissions, workload might be more manageable and discharges might occur in a more uniform and predictable manner (Arora et al., 2008).

We also compared team discharge rates in the first week, last week and remaining weeks of a resident rotation schedule and found no substantive differences. This finding may be in part because of attending physician scheduling. Since attending physicians lead team decision-making but do not follow the resident rotation schedule, similar rates
of discharge during the course of the resident rotation schedule may not be surprising. A study by Smith et al did find that the last three days of the month was an independent predictor of LOS (Smith et al., 2002). Lastly, we observed that individual attending physicians had small but significant differences in discharge rates and found that attending physicians with shorter coverage periods tended to have lower discharge rates compared to attending physicians with longer coverage periods. Physicians who attend for longer periods of time may be more invested in discharge processes and discharge planning. Further study is required to investigate optimum scheduling and durations of attending coverage to improve efficiency.

Limitations of this study

This study has several limitations. It took place in one large teaching institution with resident and attending physician staffing, and as a consequence, may be less generalizable to other community hospitals. Nonetheless, clinical scheduling policies and availability of resources on weekends and holidays affect all hospitals. Also, we excluded the period December 16th – January 14th from our analyses due to Christmas/New Year holiday disruptions to physician team structures and holidays not landing on a Monday. Therefore, while our results may underestimate the impact of holidays on discharge rates, they still reveal important trends in discharge rate during holidays.
Conclusion

In conclusion, our findings suggest that day of the week, holiday status, and team admission schedule significantly influenced daily discharge rates. Individual attending physicians and their length of coverage have a small influence in discharge rate. Introducing greater holiday and weekend capacity as well as reorganizing internal processes such as admitting and attending schedules may potentially optimize discharge rates. Discharge rate, expressed as the number of discharges divided by census on a particular day, may be a useful metric to measure the impact of operational factors on the discharge process.
ABSTRACT

Background: Timely access to emergent patient care is an important quality and efficiency issue. Reduced discharges of inpatients on weekends are a prevalent reality to many hospitals and may reduce hospital efficiency and contribute to Emergency Department (ED) congestion.

Objective: To evaluate the daily number of ED beds occupied by inpatients after evenly distributing inpatient discharges over the course of the week using a computer simulation model.

Methods: System dynamics simulation modeling study from a tertiary academic care hospital in Toronto, Canada. Daily historical data from the General Internal Medicine (GIM) Department between January 15th to December 15th for two years, 2005 and 2006 were used for model building and validation, respectively.

Results: A system dynamics simulation model was built to test smoothing discharges over the course of the week. There was good agreement between model simulations and historical data for both ED and ward censuses and their respective lengths of stay, with the greatest difference being +7.8% for GIM ward length of stay (model: 9.3 days versus

historical: 8.7 days). When discharges were smoothed across the seven days, the number of ED beds occupied by GIM patients decreased by ~27-57% while ED length of stay decreased 7-14 hours. The model demonstrated that patients occupying hospital beds who no longer require acute care have a considerable impact on ED and ward beds.

**Conclusions:** Smoothing out inpatient discharges over the course of a week had a positive effect on decreasing the number of ED beds occupied by admitted patients. Despite the particular challenges associated with discharge home and/or transfer to external facilities on weekends, simulation experiments suggest that discharging these patients evenly across the week may significantly reduce bed requirements and length of stay in the ED.
The purpose of this chapter is to:

1. Develop and validate a computer simulation model that mimics the movement of patients admitted from the ED.

2. Examine the reduction in ED crowding through smoothing discharges over the entire week without changing the number of patients discharged.

4.1 INTRODUCTION

Admitted patients in the emergency department (ED) are associated with ED overcrowding (Schull et al., 2002; Canadian Institute for Health Information, 2007). They are also a symptom of inefficient hospital operations, contributing to more costly care, increased waiting time and general operational congestion. Striving for efficient hospital operations is a common goal within any healthcare organization and striking a balance between demand, capacity and revenue is key in achieving this efficiency. Two prime examples of inefficient hospital operations are the occupation of acute care beds by patients who no longer require acute care (Black and Pearson, 2002) and the disproportionate allocation of discharge resources to weekdays compared to weekends (Bell and Redelmeier, 2004). To what extent does lack of weekend discharges affect bed capacity requirements? Would increased weekend discharges free up ED and inpatient beds? Bell and Redelmeier have suggested that increasing weekend hospital capacity can achieve an increase in procedure volumes by ~15%, decrease procedure waiting times, and may ultimately reduce length of stay (Bell and Redelmeier, 2005).
Recognizing inefficiencies within health care systems is a first step. The next step is to understand the factors that influence and contribute to these inefficiencies (Wolstenholme et al., 2007). System dynamics computer simulation is a tool in health care system design and operations that has gained momentum over the last several years (Young, 2005; Eldabi et al., 2007). This tool allows for the users to simplify the complexities of healthcare operations and study cause and effect relationships among influencing factors. Simulation attempts to reproduce events as they occur in the real world allowing the user to eliminate the static and noise from real world operations to observe and test the results of change. The intention is to imitate the operation of a health care setting inside a computer and to test various operating strategies before real-world implementation. System dynamics was originally designed as a qualitative tool to provide understanding of large systems. Entities are modeled as continuous quantities, rather like a fluid flowing through a system of reservoirs or tanks connected by pipes (Sterman, 2000). Patients "flow" through a network along lines with specified "rates" (either constant or based on a formula) and accumulate at points called levels or stocks. Applications of system dynamics in health care are diverse and include models of acute care hospitals (Brailsford et al., 2004; Lane and Husemann, 2008), the Emergency Department (Lane et al., 2000), cardiac catheterization services (Taylor and Dangerfield, 2005), diagnostic laboratories (Rohleder et al., 2007), social care (Royston et al., 1999) (Wolstenholme, 1999), and public health issues (Homer and Hirsch, 2006) (Midgley, 2006).

System dynamics modeling may be used to predict effects of system changes. However, to the best of our knowledge, no previous studies have used simulation to
quantify the impact of increased weekend discharges on ED and inpatient bed requirements. To what extent does lack of weekend discharges affect bed capacity requirements? Would increased weekend discharges free up ED and inpatient beds? Bell and Redelmeier have suggested that even conservative growth in weekend service can achieve an increase in procedure volumes of ~15% (Bell and Redelmeier, 2005). To address this gap in research, we develop and validate a computer simulation model that mimics the movement of patients admitted from the ED and quantifies bed savings after increasing weekend discharges.
4.2 MATERIALS AND METHODS

The computer simulation models the General Internal Medicine (GIM) program of a large tertiary care centre and teaching hospital. 98% of GIM patients are admitted from the Emergency Department (ED), accounting for nearly 50% of all ED inpatient admissions. GIM patients often block ED beds waiting to be transferred to an inpatient bed within the hospital. At any point in time, significant proportions (~25%) of GIM patients are ready to be discharged but remain in hospital awaiting post-acute care placement in the community.

Model Derivation

We built the model using data from all patients (2577 inpatient admissions) who received care from GIM during the 335-day study period (January 15th 2005 to December 15th 2005) at the Toronto General Hospital. We classified GIM inpatient admissions into patient categories based on their visit disposition of either “Discharge Home”, “Discharge Inter-facility” (discharge to an external facility), or “Discharge Other” (includes intra-facility transfers, in-hospital deaths, and left against medical advice).

For each day of the derivation cohort, the set of GIM service-level variables required for the simulation include: (1) number of ED visits, (2) ED visit admission proportion (expressed as the proportion of ED visits admitted to GIM over the course of the next 24 hours), and (3) discharge proportions. For each of the three patient categories, the discharge proportion is the ratio of GIM patients discharged over 24 hours to the GIM census at 8AM in that category. From these daily values, day of week averages were computed and served as model inputs. We also determined the
distributions of admission and discharge proportions by hour of the day and day of week for each patient category (Figure 4.1). The different patient categories have the same pattern of admission (Figure 4.1A) yet different pattern of discharge (Figure 4.1B); within a patient category, the hourly pattern is similar by day of week [as illustrated for the representative home patient category admission pattern (Figure 4.1C) and discharge pattern (Figure 4.1D)]. Based on these observations, a combined admission pattern by week and by hour was used for all patient categories, and a unique discharge pattern by week and by hour was used for each patient category.

We built the system dynamics simulation model based on the above inputs using the commercially available software Vensim, version 5.2a (Ventana Systems Inc., Harvard, MA). We chose a time-step of 0.05 hours (3 min). To exclude initialization transients, the model was run for eight simulated weeks, yielding a repeating 7 day 24 hour cycle, or ‘steady state’. The model simulated a one-week period, and outcome measures were calculated from the steady state region. The model output was 8AM GIM census (defined as the number of patients at 8AM that are under the care of GIM services) occupying ED and ward beds, and average GIM length of stay in the ED (defined as the time between decision to admit to GIM and transfer to ward or discharge from ED) and in the ward (defined as the time between GIM transfer to ward and discharge from ward). The study received approval from the University Health Network Research Ethics Board.
Figure 4.1: (A) ED visit admission proportions to GIM and (B) GIM discharge proportions in hourly slots, grouped by patient categories. (C) ED visit admission proportion to GIM (home category) and (D) GIM discharge proportion (home category) in hourly slots, grouped by days of the week. Data from January 15th – December 15th 2006.
Model Validation

The purpose of model validation is to provide stakeholders with assurance that the model accurately reflects the system it is trying to mimic. Model validation was carried out qualitatively throughout the modeling process and quantitatively via simulation runs. Staff physicians were engaged, and their expert feedback was incorporated, in the development of the structure, assumptions, and feedback relationships of the model to ensure validity. To quantitatively validate the model, we ran the model using 2006 input variables from the period January 15th to December 15th 2006, and compared the model output with 2006 historical output measures that had not been used in the construction of the model.

Scenario Testing

Following model validation, we performed a number of simulation experiments. Our strategy was to quantitatively show the effect of smoothing discharge rates on occupancy and length of stay. To compare scenarios, we used the model built with 2006 inputs as a baseline case. We developed 2 scenarios designed to smooth discharges over the course of the week while maintaining the total discharges the same (Figure 4.2). The first scenario, “Smoothed Average Case” simply redistributes current discharges evenly across days of the week by applying the 7-day average discharge proportion to each day. The second scenario, “Every Day is a Weekday Case” mimics “Smoothed Average Case” but instead of using the 7-day (weekly) average discharge proportion, we use the 5-day (weekday) average discharge proportion.
Figure 4.2: Strategy for Scenario Testing. Assuming a hypothetical occupancy of 100 patients and a Base Case discharge proportion of 5% on Sunday, 10% on Monday-Thursday, 20% on Friday, and 5% on Saturday; in the “Smoothed Average Case”, we apply the average weekly Base Case discharge proportion \((5\% + 10\% + 10\% + 10\% + 10\% + 20\% + 5\%)/7 = 10\%\) to each day of the week. In the “Every Day is a Weekday Case”, we apply the average weekday Base Case discharge proportion \((10\% + 10\% + 10\% + 10\% + 20\%)/5 = 12\%\) to each day of the week. Since total discharges = census x discharge proportion, in “Every Day is a Weekday Case”, increasing the discharge proportion while maintaining the same number of total discharges results in a decrease in census.
Since the weekday average is greater than the weekly average, we expect that in “Every Day is a Weekday Case” patients are discharged a little faster and as a result, census decreases. We focused on “Discharge Home” and “Inter-facility Transfers” because they represented a large proportion of patient volumes (73% home, 13% inter-facility) and patient days (55% home, 28% inter-facility) (Figure 4.3) and exhibited day of the week discharge trends. We excluded scenarios involving the patient category designated “Other” [in-hospital deaths and left against medical advice patients (not amenable to increased weekend discharges), and intra-facility transfer patients (a small category and historically did not exhibit day of the week transfer trends)].
Figure 4.3: Percent GIM patient days versus percent GIM patient admissions for the various GIM patient categories. Data from January 15th – December 15th 2005 and 2006.
4.3 RESULTS

Model Structure

Figure 4.4 displays a simplified structure of the system dynamics model. We model GIM patient flow from inpatient admission and up to discharge from GIM services. At the centre of the model are the GIM patient stocks (or levels) and flows (or rates) that together portray the physical flow of GIM patients from the ED and to the GIM ward. The model incorporates exogenous factors that influence flow rates which in turn change stock levels. These include the daily number of “ED Visits”, “ED Visit Admission Proportion”, GIM admission proportions by patient category (“GIM Proportion Home”, “GIM Proportion Inter-facility”, and “GIM Proportion Other”), “Discharge Proportion Inter-facility”, and “Discharge Proportion Other”. For example, “GIM Admission Rate” is calculated by multiplying two exogenous variables “ED Visits” and “ED Visit Admission Proportion”. Increasing the value of “ED Visits” will increase the “GIM Admission Rate” which results in a larger stock of “GIM in ED”.
**Figure 4.4:** Simplified representation of the system dynamics simulation model structure. Patients are admitted to GIM via the Emergency Department (ED) and board in the ED until they are transferred out to an inpatient ward or discharged from the ED. GIM patients are classified in this model according to discharge disposition of: discharge home, inter-facility transfer, and discharge other (includes intra-facility transfer, death and left against medical advice).
To represent important identified ED-GIM relationships, we introduced three functions derived from historical hospital data from the 2005 study period to the model (Figure 4.5). The first function, “Bed-Turn-Around Time”, describes the relationship between the timing of ward discharge and the timing of ED transfer to ward (Figure 4.5A). In practice, this transfer out rate depends on bed availability on the GIM ward. In the model, this rate is formulated as the ward discharge rate with a time delay (“Bed-Turn-Around Time”) that incorporates time required by housekeeping to prepare the bed and for nursing to accept the new patient. As the number of ward discharges increases, “GIM Discharge from Ward”, the time delay to transfer a new patient to the ward “Bed Turn-Around-Time” also increases.

The second function, “Discharge from ED Probability”, describes the situation when GIM patients board so long in the ED that they become sufficiently stable to discharge (Figure 4.5B). In the model, the rate at which GIM patients are discharged from the ED depends on the occupancy of GIM patients boarding in the ED. The probability of being discharged from the ED increases as the occupancy of GIM boarders in the ED increases.

The third function, “Alternate Level of Care Occupancy”, describes the relationship between discharge rate and ward census occupied by patients who no longer require acute care (Figure 4.5C). While the decision to discharge an individual patient from hospital should predominately be a clinical one, discharge depends on internal hospital factors as well as external community factors. One major factor is the availability of alternate level of care (ALC).
Figure 4.5: Three functions derived from historical hospital data from the 2005 study period to the model. (A) “Bed-Turn-Around Time”, describes the relationship between the timing of ward discharge and the timing of ED transfer to ward. (B) “Discharge from ED Probability”, describes the situation when GIM patients board so long in the ED that they become sufficiently stable to discharge. (C) “Alternate Level of Care Occupancy”, describes the relationship between discharge rate and ward census occupied by patients who no longer require acute care.
ALC patients no longer require acute care but wait in hospital because a more appropriate care setting (long-term care, complex continuing care, convalescent care, rehabilitation care, home care, or palliative care) is not available. ALC patients decrease the working capacity of the ward - the proportion of patient census that have active issues and whose care plan is driven by physicians and the care team. Physicians and care teams have effectively no ability to influence the discharge process of ALC patients, and as a result, fewer aggregate discharges take place. In the model, we approximate ALC occupancy with the stock of inter-facility transfer patients. The rate at which GIM patients are discharged home in the model decreases as “Alternate Level of Care Occupancy” increases.

**Model Validation**

The model was quantitatively validated by comparing model outcome measures (GIM census at 8AM and GIM length of stay) with actual historical GIM census at 8AM and GIM length of stay for the 2006 study period (Table 4.1). There is good agreement between model simulations and historical data for both ED and ward censuses and their respective lengths of stay, with the greatest difference being +7.8% for GIM ward length of stay (model: 9.3 days versus historical: 8.7 days).
Table 4.1: Model Validation

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<thead>
<tr>
<th>Metric</th>
<th>2006</th>
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<tr>
<td></td>
<td>Model (Base Case)</td>
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<tr>
<td>8AM Census (patients)</td>
<td>Total GIM 67.1</td>
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<tr>
<td></td>
<td>GIM in ED 7.6</td>
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<tr>
<td></td>
<td>GIM in Ward 60.0</td>
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<tr>
<td>Length of stay (days)</td>
<td>Total GIM 8.4</td>
</tr>
<tr>
<td></td>
<td>GIM in ED 1.0</td>
</tr>
<tr>
<td></td>
<td>GIM in Ward 9.3</td>
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</tbody>
</table>

Scenario Testing

To quantitatively test the effect of smoothed discharges, we simulated four scenarios: (1) “Smoothed Average Case” applied to home discharge patients, (2) “Smoothed Average Case” applied to both home discharges and inter-facility transfer discharges, (3) “Every Day is a Weekday Case” applied to home discharge patients, and (4) “Every Day is a Weekday Case” applied to both home discharges and inter-facility transfer discharges. Table 4.2 compares census, weekly discharges, and length of stay for all four scenarios to base case.

In the “Smoothed Average Case” scenario where everyday was the average weekly Monday-Sunday base case discharge proportion, both the “Smoothed Average Case” scenarios resulted in similar outcome measures. Both reduced the “GIM in ED” stock by ~27% (from 7.4 patients to 5.4 patients) and GIM in ED length of stay by ~31% (from 24 hours to 17 hours).

In “Every Day is a Weekday Case” scenarios, weekend discharge proportions were raised to levels equal to weekdays (everyday at average weekday Monday-Friday base case discharge proportion). As expected, substantially larger reductions in “GIM in ED” stock were achieved. When only home discharges were smoothed, GIM in ED decreased 48% compared to base case. Correspondingly, GIM in ED length of stay decreased 51% (from 24 hours to 12 hours) and GIM ward length of stay decreased 13% (from 9.5 days to 8.2 days). Combined smoothing of home and inter-facility transfers further reduced the “GIM in ED” stock and length of stay by an additional 10% compared to the same scenario applied only to home discharges.
<table>
<thead>
<tr>
<th>Table 4.2: Scenario Tests</th>
<th>“Smoothed Average Case”</th>
<th>“Every Day is a Weekday Case”</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Base</td>
<td>Home Discharges</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Home</td>
</tr>
<tr>
<td><strong>8AM Census (patients)</strong></td>
<td>Total GIM</td>
<td>67.1</td>
</tr>
<tr>
<td></td>
<td>GIM in ED</td>
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<td></td>
<td>GIM in Ward</td>
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<tr>
<td></td>
<td>Home</td>
<td>34.4</td>
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<tr>
<td></td>
<td>Inter</td>
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</tr>
<tr>
<td><strong>Sum Weekly Discharges</strong></td>
<td>Total GIM</td>
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<td>GIM in ED</td>
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</tr>
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<td></td>
<td>GIM in Ward</td>
<td>44.8</td>
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<tr>
<td></td>
<td>Home</td>
<td>32.8</td>
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<tr>
<td></td>
<td>Inter</td>
<td>5.9</td>
</tr>
<tr>
<td><strong>Length of stay (days)</strong></td>
<td>Total GIM</td>
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</tr>
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<td></td>
<td>GIM in ED</td>
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<td></td>
<td>GIM in Ward</td>
<td>9.5</td>
</tr>
<tr>
<td></td>
<td>Home</td>
<td>7.4</td>
</tr>
<tr>
<td></td>
<td>Inter</td>
<td>19.7</td>
</tr>
</tbody>
</table>

Scenario Tests: “Smoothed Average Case”: Everyday at smoothed average weekly (Sunday-Saturday) base case discharge proportion; “Every Day is a Weekday Case”: Everyday at average weekday (Monday-Friday) base case discharge proportion.
With respect to daily changes in “GIM in ED” census, Figure 4.6 displays the effects seen with the two scenarios applied to home discharges compared to base case. Both scenarios when compared to base case decrease and stabilize the “GIM in ED” stock. In contrast to “Every Day is a Weekday Case”, where there is an across the board reduction compared to base case, a cross-over between base case and “Smoothed Average Case” occurs on Friday.
Figure 4.6: Model output GIM in ED for Scenarios “Smoothed Average Case” and “Every Day is a Weekday Case” applied to home discharges, compared with base case. “Smoothed Average Case”: Everyday at average weekly (Sunday-Saturday) base case discharge proportion home; “Every Day is a Weekday Case”: Everyday at average weekday (Monday-Friday) base case discharge proportion home.
4.4 DISCUSSION

This paper is the first to describe the design, construction and validation of a system dynamics computer simulation that uses patient flow to examine the effect of increasing weekend inpatient discharge productivity on ED and ward bed requirements. There are three main findings from this study.

First, we were able to validate a system dynamics simulation modeling of ED and GIM. Model-generated census and length of stay in ED and on the GIM ward corresponded well with historical data. We were able to test scenarios that smoothed discharges over the course of the week and understand the implications of these tests on ED and GIM performance metrics.

Second, smoothing discharges over the course of the entire week while keeping the total number of patients discharged in the week unchanged, resulted in fewer ED beds occupied by GIM patients and reduced GIM length of stay. Percent reductions in length of stay were most significantly felt in the ED where durations of stay are measured in hours as opposed to days on the ward. Studies have shown that decreased availability of resources on weekends is associated with delays in discharge and as a result, increased length of stay (Earnest et al., 2006). In fact, the phenomenon of average length of stay varying by day of admission is caused mainly by day of the week variation in discharge activity. Typically, Friday is the most common day of discharge, and it has been suggested that availability of hospital resources including physicians and hospital staff are decreased on weekends. To avoid the weekend, patients were preferably discharged on Friday (Varnava et al., 2002). In addition to bed savings, smoothing discharges may positively impact quality of care. van Walraven and Bell have shown that patients
discharged on Fridays had an increased independent risk of death or non-elective hospital readmission within 30 days after discharge (van Walraven and Bell, 2002). They speculate that patients discharged on Friday were either less medically stable, or that the discharge preparation was incomplete owing to competing demands on clinicians’ and hospital staff’s time from multiple discharges on Fridays, or that there were delays in implementing social services. They suggest that clinicians keep this observation in mind before they consider releasing patients home for the weekend.

Third, the model demonstrates that accumulation of ALC patients cause congestion and reduce the working capacity on the ward. Unlike “Discharge Home” patients which represent the group that physicians and discharge planners can best manage by working with family and home care providers, ALC patients more often need to wait for a bed in a rehabilitation or long term care facility which involves external acceptance approval processes. The model shows that reducing the number of ALC patients via earlier discharge significantly decreases the number of ED beds occupied by GIM patients. A recent study by Carey et al. to quantify and characterize delays in care for general medicine patients supports this conclusion. They found that 84% of non-medical service delays on their general medicine teaching service were due to waiting for placement in a skilled nursing facility (Carey et al., 2005). As the patient population ages and more patients require care in an ALC setting, we should anticipate the need for additional beds even if admission volumes remain static (George et al., 2006). A dedicated ward for immediate transfer of patients that no longer require an acute care services has been previously shown to reduce the use of acute care hospital beds by a median of 11 days per patient (Crotty et al., 2005).
The authors acknowledge that smoothing discharges into the weekend timeframe has a larger impact than just re-allocating work. Currently, few weekend discharges take place for a variety of reasons. For patients discharged to a home setting, lack of hospital staff (physicians, social workers, physiotherapists, and occupational therapists), decreased capacity to perform investigations (laboratory tests, procedures, consults), and reduced coordination of community resources (home care, transportation, professional services) can reduce weekend discharge rates. For patients requiring transfer to post-acute care facilities, in our experience, few facilities have the resource capacity to accept new patients on weekends, making weekend transfers nearly non-existent. Trying to make changes suggested by this paper would require careful consideration on a variety of levels for the various sectors of care. Considerations include, but are not limited to, human resources, scheduling, salary and union implications, quality of life, and change management.

**Limitations**

Like all models, ours is a simplification of reality and is based on assumptions from historical data validated with the expert opinions of experienced GIM physicians. As such, we made generalizations and simplifications in the model. We used the average weekly pattern for hourly admissions and discharges instead of individual day-of-week patterns. We also divided GIM patients into categories upon transfer out of ED whereas realistically, time of patient category designation is not well-defined. The real world is more complex than the proposed model, partly explaining the difference between historical and model output in our validation exercise.
Although the results presented here are based on institutional data, our model is based on one inpatient service of one institution. Other inpatient services and acute care hospital sites may experience different characteristics and require specific inputs to measure results in their institution. Therefore, in order to make our findings more generalizable, testing this model on other hospital datasets is required to confirm appropriateness of model constructs. In addition, interventional studies may be carried out within TGH GIM to determine if outcome measures predicted in the model are substantiated in real life. Examples of interventions include establishing a partnership with a long-term care facility that supports the appropriate transition to its facility seven days a week, implementing a weekend social worker, and putting into practice a policy that allows physicians on-call during weekends to discharge patients from other teams.

Conclusion

The goal of this study was to provide quantitative support for the smoothing of inpatient discharges over the entire week (instead of increasing total inpatient discharges, as usually proposed) to reduce the number of inpatient boarders in the Emergency Department. By accurately depicting feedback interactions within the ED-GIM system using system dynamics simulation, we showed that simply redistributing discharges over the course of the week could have a positive effect on decreasing the number of ED beds occupied by inpatient boarders. Despite the particular challenges associated with discharge home and/or transfer to external facilities on weekends, system dynamics simulation experiments suggest that discharging these patients evenly across the week may significantly reduce bed requirements and length of stay in the ED.
There is tremendous opportunity for simulation to be applied to other health care settings. The model presented here is generalizable and can be extended to address other questions concerning the management of hospital capacity and estimates of future resource needs. This paper will be used as a platform to further investigate the cultural and organizational barriers to implementing 7-day a week discharges. In addition it will be used to begin a dialogue with the post acute care centres and home support agencies in effort to bring transparency to an overall systems approach in developing operational efficiencies in all healthcare organizations involved in the continuum of care.

**What is already known on this topic**

Decreased availability of resources on weekends is associated with delays in discharge, increased length of stay, and emergency department congestion. Emergency department congestion is exacerbated by patients occupying hospital beds waiting for care in the community.

No previous studies have used simulation to quantify the potential impact of increased weekend discharges from hospital to community on emergency department and inpatient bed requirements.

**What this study adds**

Our study suggests that system dynamics simulation modeling can accurately mimic the movement of patients admitted from the ED, transferred to the inpatient ward, and discharged from hospital.
This modelling predicts that smoothing discharges over the course of the week may substantially decrease the number of inpatient boarders in the emergency department and reduce overall length of stay. The model also demonstrates that patients occupying hospital beds who no longer require acute care have a considerable impact on ED and ward beds.
CHAPTER 5
USING SYSTEM DYNAMICS PRINCIPLES FOR CONCEPTUAL MODELLING
OF PUBLICLY FUNDED HOSPITALS

ABSTRACT
This chapter examines the longstanding operational issue of patients boarding in the emergency department (ED) who have been admitted to hospital (inpatient “boarders”). From this analysis we design a conceptual model that provides a roadmap to create sustainable improvements in ED waiting times. The conceptual model is built using system dynamics methodology, and illustrates the use of system archetypes, a set of common causal feedback loops that illustrate how well intended decisions have unintentional side effects. This chapter outlines the journey taken by one large academic health centre to address these issues and highlights the larger implications and recommendations that are applicable to other publicly funded hospitals.
The purpose of this chapter is to:

1. Identify causal feedback loops found in publicly funded hospitals.
2. Create a conceptual model that clarifies and displays factors and feedback structure influencing the ED-GIM problem.
3. Describe insights and implications of the conceptual modelling process.

5.1 INTRODUCTION

Publicly funded hospitals are under increased scrutiny over the choices they make to maintain a balanced budget and how these choices translate to access for emergent and elective care. Every hospital has a unique set of population needs, community service providers and internal circumstances that, even under careful management, have the potential to result in substantial budget deficits or compromise the level of care provided to patients. Probing beyond the surface often reveals common causal themes that contribute to the relative levels of ‘success’ or ‘failure’ present in publicly funded hospitals. By identifying these causal themes, hospital management can be made more aware of how their decisions have unintentional side effects.

This chapter describes the process of taking a chronic operational problem common to many publicly funded hospitals and from it designing a conceptual model that provides a roadmap to address the problem situation. The roadmap is built with system archetypes, a set of common causal feedback loops that illustrate how well intended decisions have unintentional side effects (Wolstenholme, 2003). The objectives of this chapter are to share one hospital’s journey from symptomatic chaos to a clear understanding of the problem; to illustrate the insights gained and strategies redesigned as
a result of the conceptual modelling process, and to describe implications for publicly funded hospitals.
5.2 THE PROBLEM AS DESCRIBED BY THE HOSPITAL

The chronic operational problem concerned Toronto General Hospital (TGH), one of three hospitals of the University Health Network (UHN), one of Canada's largest acute care teaching hospitals. Like all publicly funded hospitals, TGH must balance competing priorities for timely access to quality scheduled (elective) and unscheduled (emergent) patient care. In recent years at TGH, it has been common for more than half of Emergency Department (ED) stretchers to be occupied by patients admitted to one service, General Internal Medicine (GIM). These patients are waiting on average over 20 hours to be transferred to ward beds, and are known as inpatient “boarders”. It is well documented in the literature that inpatient boarders are the most significant contributing factor to ED congestion and excessive ED length of stay (Olshaker and Rathlev, 2006; Moskop et al., 2009).

This study addresses the chronic operational problem of ED boarders, referred to as the ‘ED-GIM problem’ and sets about creating a conceptual model that provides a roadmap for communication, debate, shared understanding and recommendations for sustainable improvements in ED waiting times.
5.3 BRIEF OVERVIEW OF SYSTEM DYNAMICS AND SYSTEM ARCHETYPES

A conceptual model is a coherent and unifying theory of behaviour taken from bits of information about the real world (Wolstenholme, 1992; Robinson, 2008). The rigorous structural framework within system dynamics is helpful in eliciting and displaying information used to build a conceptual model (Forrester, 1994; Lane and Oliva, 1998). At the core of system dynamics methodology are the concepts of feedback loops and time delays that characterize the dynamic complexity of a system (Sterman, 2000). Causal loop maps are often used to convey these elements (Montibeller and Belton, 2006).

In many instances, the detail of comprehensive causal loop maps may overwhelm the intended audience and prove more of a distraction rather than a tool to focus attention on feedback interactions within a system. To improve their usability, Wolstenholme has proposed a set of generic two-loop archetypes that characterize all counter-intuitive behaviour or unintended consequences (Wolstenholme, 2003). One loop is the intended consequence feedback loop and the second loop is the unintended consequence feedback loop. A delay exists before the unintended consequence manifests itself and an organizational boundary ‘hides’ the unintended consequence from the ‘view’ of those initiating the intended consequences (Wolstenholme, 2004).

The tools of system dynamics have been extensively applied to solve important real world problems in health care. Applications of system dynamics mapping models in health care include models of acute patient flows (Wolstenholme et al., 2007; Lane and
Husemann, 2008), community care (Wolstenholme, 1993) and short-term patient flows (Coyle, 2000).
5.4 UNDERSTANDING THE PROBLEM

Part of designing a conceptual model of ED-GIM is gaining a clear understanding of the ‘ED-GIM problem’. Discussions with clinicians and hospital management were held to extract individual views and brainstorm reasons for the problem. All stakeholders agreed that the trend in increasing ED boarders left unresolved would negatively impact quality of care and satisfaction of patients and staff. However, each presented a different view on the root cause of the problem.

One opinion was that the increasing number of GIM boarders in the ED was primarily due to external factors out of hospital control. This included a patient population that was aging and required more frequent hospitalization. Also, lack of downstream capacity to accommodate the post-acute care needs of this aging population meant that patients would remain in GIM beds when they no longer required acute care. This effectively decreases the working capacity of the GIM ward and creates a backlog of patients in the ED.

Another opinion was that the problem had arisen from hospital internal inefficiencies. TGH had recently embarked upon a clinical process improvement project using Lean methodologies (Caesar et al., 2008). Successful initiatives included the standardization of morning rounds to include timelines for follow-up and discharge planning, and the tightening of hand-off points between a patient emptying a ward bed and the next ED patient assigned to it. While these initiatives eliminated some delays experienced in the ED-GIM patient pathway, the issue of GIM boarders in the ED persisted. It was suggested that significant reductions in GIM boarders could be achieved
if focus was placed on eliminating organizational operational inefficiencies including more timely access to medical imaging, lab results and consultations.

Another opinion supported this view of looking internally within the hospital for the root of the problem but felt that other admitting services had a large part to play in the growing number of GIM boarders. With the UHN aggressively pursuing more volume-based revenues, there was growing belief within globally-funded services that specialty services receiving volume-based revenues were now less inclined to admit emergent medical patients. By declining to admit to their service, often these patients would be admitted to GIM which is funded from the global budget. Could the rapid increase in GIM boarders be associated to recent trends in funding?

As the number of meetings grew, stakeholders built on individual views, triggered new thoughts, and saw gaps in the association of ideas. To structure the large number of issues and concerns brought forth while discussing the ED-GIM problem, a main issues diagram using the “magnetic hexagons” general problem-structuring procedure (Hodgson, 1992; Lane, 1993), was extracted (Figure 5.1):
Figure 5.1: Main issues confronting hospital management
Three clusters of main issues were extracted:

- Changing patient population outlines three difficulties: technology has allowed more care to take place in the outpatient setting; newer drugs and approaches allow people to live longer periods of time in a chronic state (for example, diabetes, cancer, heart failure); a rapidly aging population that consumes a disproportionate amount of health care resources.

- Resource allocation & work environment involves the relationship between internal hospital resources (number of beds, bed occupancy, staffing levels), external health care capacity in the community (long-term care, home care, rehabilitation) and their impact on hospital operational efficiency (length of stay, staff productivity, variations in discharge).

- Ministry of Health accountabilities defines the performance obligations of the hospital, including balancing the budget, meeting system access targets (volumes and wait times) and providing a high level of care.
5.5 **KEY CAUSAL RELATIONSHIPS**

This section illustrates the key causal relationships within and between the three clusters of main issues impacting ED-GIM. The elicited relationships underwent a process of clarification, correction and refinement until a consensus was reached between the stakeholders.

*Changing patient population*

At the core of the changing patient population cluster is a reinforcing loop stimulated by an aging population (Figure 5.2). As the aging population grows, they are more prone to develop multiple chronic illnesses that have potential to develop into acute disease, requiring hospital inpatient admission (Romanow, 2002). Inpatient admission combined with advances in medicine, including new and improved diagnostic and therapeutic technologies, results in increased treatment intensity. As treatment intensity increases, there is a greater likelihood of recovery. Recovery or survival increases the aging population. This circle of causality reinforces itself and is termed the silver tsunami (Delafuente, 2009). Also, as the aging population grows, there is greater demand for post-acute care in the community. Patients occupying acute care beds waiting for post-acute care are deemed “alternate level of care” or ALC and are a significant downstream contributor to ED boarders (Canadian Institute for Health Information, 2009a).

Advances in medicine also impact an additional reinforcing loop (Figure 5.3). New therapeutic technologies and changes in clinical practice contribute to hospitals shifting some types of care from inpatient to same-day or outpatient care.
Figure 5.2: Silver tsunami

Figure 5.3: Reduction of capacity translates to higher acuity
Outpatient care as opposed to inpatient care can contribute to positive outcomes, such as improvements in patient care and reduction in hospital costs and total inpatient days (Gregoroff et al., 2004; Fedorowicz et al., 2005). A reduction in inpatient days allows for potential reductions to inpatient capacity. Inpatient capacity reductions combined with the success of outpatient care reinforces more medical advances in outpatient treatment options. The unintended consequence is that a reduction of inpatient capacity translates to more stringent admission criteria, whereby only patients with the highest acuity levels are admitted. As patients become more acute and illness burden increases, length of stay increases, effectively increasing occupancy or capacity utilization. In addition to length of stay, resource consumption, staff workload, and the costs of care also increase (Poole et al., 1998). Sustained levels of high bed occupancy will likely trigger an investment in more beds, but this response is delayed, often taking months to years to be realized.

Ministry of Health accountabilities

At the core of the Ministry of Health accountabilities cluster is a reinforcing loop stimulated by the hospital’s deficit gap (Figure 5.4). Revenue generated from the Ministry of Health comes either in the form of global-based revenue or volume-based revenue. If the deficit gap (difference between total revenue and total expense) is low, a virtuous circle is stimulated: small deficits lead to a reputation of fiscal responsibility, which is more likely to attract additional Ministry of Health revenue. The more revenue a hospital has at its disposal, the more it can allocate to debt reduction, further promoting itself as a financially responsible hospital.
Figure 5.4: Balancing budget
One strategy to attract additional Ministry of Health revenue is to establish a Centre of Excellence in a certain area of care. Recently, the Ministry of Health has set aside volume-based funding for targeted initiatives such as the Wait Times Strategy (a variety of surgeries that have lengthy wait lists and waiting times, including hip and knee, cataract, certain cancer and cardiac surgeries) and Priority Programs (for example, chronic kidney disease, organ transplantation, and critical care). UHN has created and sustained a virtual reinforcing centre for excellence in specialty care loop stimulated with specialty services infrastructure and Ministry of Health volume-based revenue (Figure 5.5). Well-established infrastructure allows more procedural cases to be performed, which in turn attracts proceduralists from other hospitals to transfer their privileges. Highly skilled proceduralists raise the hospital’s reputation as a centre for excellence in specialty care, and attract additional ministry revenue to continue expansion of specialty services infrastructure. The unintended but inevitable consequence is downstream unfunded demand for reoccurring medical inpatient care generated from these complex procedural cases. Examples include surgical oncology patients admitted with treatment complications and cardiac surgery patients with worsening heart failure. Unlike the initial revenue-generating procedure, subsequent medical inpatient care is not specifically funded and the costs of care must be covered using the global budget. What is more, as capacity utilization on the medical wards reaches capacity, the specialty service wards must accommodate medical overflow. As capacity utilization on the specialty wards increase, this limits the number of procedural cases that can be performed and volume-based revenue that can be generated.
Figure 5.5: Limits to revenue generation
In addition to Ministry of Health volume-based funding initiatives are initiatives to improve Emergency Department waiting times (Figure 5.6). The Emergency Department Pay-for-Results Program funds hospitals that achieve service outcomes (prescribed ED length of stay targets according to triage categories) that satisfy the conditions of funding. The predominant contributing factor to lengthy ED waiting times is the number of ED boarders. As ED waiting times increase, a Ministry of Health Pay-for-Results clawback of funding is likely to occur. In order to meet Pay-for-Results targets, three strategies are employed on a daily basis at TGH to reduce the number of ED boarders.

First, staff may try to aggressively discharge patients to reduce the number of ED boarders. Unfortunately, overly aggressive discharge of patients can contribute to less favourable outcomes, including sub-optimal quality of care, uncoordinated post-discharge planning and higher rates of readmission which ultimately increase ED boarders.

Second, managers may borrow specialty service beds, otherwise known as bed-spacing, to accommodate the backlog of ED boarders. Bed-spacing improves ED waiting times at a cost to specialty service patients whose procedures may be delayed or cancelled due to lack of bed availability. An unintended consequence is that patients waiting for their procedure to be rescheduled may become acutely ill and must access the hospital system as emergencies, ultimately increasing ED boarders.

Third, managers may open unbudgeted beds, physical beds that lack budgeted staff, to lessen the burden of ED boarders. This increases the patient-staff ratio with existing staff assuming a heavier workload.
Figure 5.6: Dealing with ED boarders
What results is an increase in length of stay, which effectively increases the number of ED boarders. An explanation for this phenomenon is described in greater detail in the next section (Resource allocation and work environment).

We have described how revenue generation in areas of excellence has been used as a strategy to balance the budget, and how it has met with unintended consequences that have limited its success. A second strategy to help balance the budget is to reduce clinical operations to budgeted levels by discouraging unfunded activity. Intuitively, scheduled care would seem to be a more appropriate candidate than unscheduled or emergent care for applying this control. However, in the case of elective procedures, a prime example of scheduled care, there is a misalignment of priorities between proceduralists and the hospital. Proceduralists manage waitlists and are reimbursed by the Ministry of Health for the number of procedures performed, so they have incentive to maximize procedures. The practice of transferring medical patients to specialty service wards is a strategy used by hospital management to reduce procedural cases to levels budgeted (Figure 5.7). The unintended consequence is the reaction of the specialty service wards- closing of their wards on weekends so that the transfer of ED boarders can not take place. In light of the current incentive structure for proceduralists, the reaction of specialty services to limit the impact of bed-spacing on their wards is both appropriate and predictable.
Figure 5.7: Specialty services work around
Resource allocation and work environment

At the core of the resource allocation and work environment cluster is hospital staff providing quality care in a productive and efficient manner which depends on their skills and motivation (Figure 5.8). High quality of care leads to staff recognition, which is satisfying and may raise the reputation of the hospital as a leading employer. As the hospital increases its attractiveness to prospective staff, this allows the hospital to be more selective in its hires.

Unfortunately, this works just as well in reverse. Poor quality, productivity or efficiency receives little staff recognition and lowers motivation. Poorly recognized and demotivated staff tend to be less satisfied with their work, and this translates to a lower level of hospital attractiveness to prospective staff. An unattractive hospital is less likely to attract highly skilled staff, leading to a vicious cycle of poor quality of care. One particular area of concern highlighted by ward managers is the association between under-resourced wards and poor quality of care. As mentioned previously, one strategy to alleviate the stress of ED boarders is to open unbudgeted beds with existing staff assuming the increased workload (higher patient-staff ratio) (Figure 5.9).

It is well-documented that high patient-staff ratios adversely impact outcomes of care (Kane et al., 2007; Garrett, 2008). To compensate, ward managers may ask staff to work overtime shifts to reduce the patient-staff ratio. However, working extra shifts likely leads to staff burnout which is frequently associated with delays in care that compromise quality and efficiency of care (Thungjaroenkul et al., 2007). Less efficient care effectively increases the patient-staff ratio.
staff skills

hospital attractiveness

quality, productivity, efficiency

staff satisfaction

staff recognition

motivation

Figure 5.8: Organizational excellence

agency and redistribution of staff

apprehensiveness in new environment

ease of navigation and problem solving

efficient care

delays in care

Figure 5.9: Patient-staff ratio strategies
Another strategy to reduce the staff-patient ratio is hiring temporary agency staff or redeploying staff from other departments within the hospital. Staff working in an unfamiliar environment are more likely to have feelings of apprehension and experience greater difficulty navigating and problem solving within the new ward. As a result, the intended consequence of hiring agency staff to reduce the patient-staff ratio is often compromised (Manias et al., 2003; Hass et al., 2006).
5.6  REDESIGN OF STRATEGIES

Figure 5.10 represents the ED-GIM conceptual model that evolved from joint discussions with clinician experts and hospital management. The conceptual model is a hypothesis of how the organizational structure of TGH, its strategies to meet performance obligations, and the demands of an aging population interact with each other and ultimately dictate the number of ED boarders. The backbone of the conceptual model is a stock-flow structure that maps out the physical flow of GIM patients admitted via the ED. At the centre is the stock of ED boarders that increases with the GIM admission rate and decreases with transfers to the GIM ward (budgeted and unbudgeted), bed-spacing to specialty wards, and direct discharge from the ED. The rates of inflow to and outflow from the stock of ED boarders are influenced by the factors diagrammed in the causal loop maps (Figs 5.1-5.9). The design of the conceptual model helped clinician experts and hospital management gain a better understanding of how hospital strategies played a part in the chronic problem of ED boarders experienced at TGH. The next step was to use the conceptual model as a roadmap in the design of sustainable strategies to improve ED waiting times.

First, the conceptual model indicates that controls applied upstream to the stock of ED boarders may potentially alleviate the ED-GIM problem. Therefore, strategies to decrease the impact of GIM safety net, ED visits and readmission (the three factors that feed into GIM admission rate) were considered. Stakeholders focused on GIM safety net for specialty services as GIM had reluctantly assumed this role as the hospital expanded its specialty services while allowing these services to “opt out” of the more complex, long-term and recurring inpatient care (Figure 5.11).
Figure 5.10: Conceptual model of the ED-GIM problem
Figure 5.11: Opting out of emergent care exacerbates the ED-GIM problem
Therefore, an in-depth analysis of trends of patients admitted to hospital, ED boarders and bed resources of 3 major admitting services at TGH for a four year period was undertaken (Wong et al., 2010a). The results indicated that the shifting admission pattern from specialty to GIM services exacerbated the number of GIM boarders in the ED.

Based on these results, clinicians and medical directors successfully redesigned two upstream strategies to control ED boarders. The first strategy was a realignment of patient volumes and redistribution of care across the hospital. This work has included revisions to the escalation policy and ED consultation guidelines that provide guidance on what conditions are appropriate for admission for each inpatient service. Significant progress has been made at TGH in reducing ED boarders and boarding length of stay since implementation of the reformed policies in September 2008. The second strategy was the redirection of the emergent oncology patient stream away from TGH ED to a more appropriate care setting. Princess Margaret Hospital, another member hospital of UHN, introduced the REACH (Reducing Emergent and Acute Care Hospitalization) acute care clinic in May 2009 so that their oncology population could access emergent care within their facility as opposed to presenting at TGH ED. The REACH clinic can initiate treatment and investigations earlier compared to a chronically backlogged TGH ED and their expertise and responsive care have proven beneficial to their patient population as well as in reducing the number of ED boarders at TGH.

Second, the conceptual model indicated that controls applied downstream to the stock of ED boarders may also potentially alleviate the ED-GIM problem. For example, inefficient processes within GIM may increase length of stay which effectively decreases
the discharge rate and subsequent rate at which ED boarders are transferred to the ward (Figure 5.12).

Therefore, an in-depth analysis of non-clinical operational factors that regulate the downstream process of discharge on the GIM service for a two year period was conducted (Wong et al., 2009). The results indicated significant variation in daily discharge rates caused by inefficient hospital processes, most notably limited weekend and holiday capacity and team admission schedules.

Based on these results, GIM clinicians considered restructuring their clinical team admitting schedule from a ‘bolus’ system, where one team accepted all new admissions on a particular day, to a ‘drip’ system, where every team accepted a share of new admissions on a particular day. The hypothesis was by replacing the ‘bolus’ admitting system with a ‘drip’ admitting system, workload might be more manageable and discharges might occur more uniformly over the course of the week. Prior to committing to such a major change in the clinical admitting structure, clinicians wanted a better idea of the quantifiable impacts of evenly distributing discharges over the course of the week on ED boarders and length of stay. Therefore, a system dynamics computer simulation was built to test various discharge smoothing strategies before real-world implementation (Wong et al., 2010b). The model demonstrated that when discharges were smoothed across the seven days, the number of ED beds occupied by GIM patients decreased by ~27-57% while ED LOS decreased 7-14 hours. With support from the simulation experiments, the GIM service moved forward with implementation of the restructured admitting schedule, and evaluation of the new system is currently underway.
Figure 5.12: Inefficient operational processes exacerbate the ED-GIM problem
5.7 RECOMMENDATIONS FROM THE CONCEPTUAL MODELLING PROCESS

Building a conceptual model of the ED-GIM problem provided awareness to clinicians and hospital management of the interdependencies of their decisions and served as a roadmap for designing sustainable strategies to deal with the problem of ED boarders. More generally, for publicly funded hospitals, the conceptual model designed recommends:

Recommendation 1: Address the root(s) of the problem, not the symptoms.

Hospital-level

Local strategies to reduce ED boarders focused on ways to move boarders out of the ED faster and included aggressive discharge, bed-spacing and opening unbudgeted beds. These strategies provided short-term symptomatic relief, but in the long-run made the matter of ED boarders worse. Alternatively, looking at strategies to prevent ED boarders proved a more successful and sustainable solution. For UHN, this included revisions to the ED admission guidelines and establishing an acute care oncology clinic (REACH clinic) within UHN’s cancer care hospital to divert presentation at the ED. In addition to looking at upstream strategies, stakeholders explored downstream strategies to improve efficiency within the GIM wards and redesigned their call schedule with the aim to smooth discharges and positively impact the number of ED boarders.
Ministry of Health-level

The Pay-for-Results program is an incentive fund for hospitals to improve ED wait times. The Ministry of Health also recognizes that the root of increasing ED boarders extends beyond the hospital and has implemented system-wide strategies to address the problem. For example, the Aging at Home Strategy operates at three levels: direct strategies (discharge coordination, transitional care teams and transitional beds), diversion strategies (palliative care outreach, supportive housing, specialized geriatric services), and preventative strategies (personal support, case coordination/system navigation, falls prevention). Recognition that care extends beyond the hospital and requires coordination across all care settings better positions the Ministry to tackle the larger systemic issue of a growing elderly population consuming increasing health care resources.

Recommendation 2: Identify and mitigate unintended consequences of decisions.

Hospital-level

Local strategies to capture volume-generated revenues by performing more scheduled procedural cases had the unintended consequence of negatively impacting unscheduled care and creating budget deficits. Aggressively pursuing volume-generated revenues resulted in increased unfunded demand for reoccurring medical inpatient care generated from these complex procedural cases. In addition, specialty services modified their emergent admitting patterns and declined to participate in bed-spacing. In the future, prior to agreeing to accept volume-generated revenues, forecasts of downstream costs (ranging from those incurred in the Emergency Department to diagnostic and
laboratory services), need to be taken into account. In this way, procedures are not performed at a loss to the hospital with the global budget being used to cover the subsequent cost when patients return for reoccurring medical inpatient care in other areas of the hospital.

**Ministry of Health-level**

System-wide strategies to reduce waiting times and wait lists for procedures involved setting aside funds for these procedures to take place. Similar to hospitals, it is critical that the Ministry of Health forecast capacity needs associated with these procedures. In the future, prior to implementing programs to achieve certain performance targets, an exploratory analysis of downstream resource requirements is necessary.
5.8 CONCLUDING REMARKS

The process of rigorously extracting a conceptual model from the mental models of clinician experts and hospital management clarified root problems, provided awareness of the interdependencies of strategic- and operational-level decisions, and guided stakeholders toward courses of action. The empowerment of clinicians and hospital managers to move forward from a better understanding of their ED congestion problem to taking action in redesigning sustainable upstream and downstream strategies to improve ED congestion within their institution is perhaps the most significant impact of this work.
CHAPTER 6

REAL TIME OPERATIONAL FEEDBACK: DAILY DISCHARGE RATE AS A NOVEL HOSPITAL EFFICIENCY METRIC

ABSTRACT

Part of delivering quality care means providing it in a timely, efficient manner. Improving the efficiency of care requires measurement. The selection of appropriate indicators that are valid and responsive is crucial to focus improvement initiatives. Indicators of operational efficiency should be conceptually simple, generated in real time, calculated using readily available hospital administrative data, granular enough to reveal detail needed to focus improvement, and correlate with other valid indicators of operational efficiency. In this paper, we propose daily discharge rate as a novel real-time metric of hospital operational discharge efficiency and compare it with average length of stay. We also suggest the use of control charts as an effective way to present daily discharge rate data to clinicians and managers in real time to prompt actionable improvements in discharge efficiency. We conclude that daily discharge rate has the potential to drive timely improvements in the discharge process and warrants consideration and further study by others interested in improving hospital operational efficiency and the delivery of quality care.
The purpose of this chapter is to:

1. Introduce a new metric to measure operational efficiency – daily discharge rate.
2. Illustrate its application and utility as a real-time indicator that is responsive to operational change and at the same time focuses on system-level effects.

6.1 INTRODUCTION

Part of delivering quality care means providing it in a timely and efficient manner (Sachdeva and Jain, 2009). For hospitals, achieving efficiency includes reducing and avoiding costs, reducing inappropriate care and unnecessary variation in processes, and removing waste found within the system (Esmail, 2007; Kuntz et al., 2007; Fraser et al., 2008). Improving hospital operational efficiency requires measurement and the selection of appropriate indicators that are valid and responsive to focus improvement initiatives. Indicators of operational efficiency should be conceptually simple, generated in real time, calculated using readily available hospital administrative data, granular enough to reveal detail needed to focus improvement, and correlate with other valid indicators of operational efficiency (Agency for Healthcare Research and Quality, 2008; Krumholz et al., 2008).

Hospital efficiency is often measured by risk-adjusted length of stay and cost per risk-adjusted discharge (Kurtz et al., 2008; Hussey et al., 2009), two data-intensive calculations that lack granularity and limit the ability to drive clinically efficient performance. There is need for meaningful real-time frontline measures that can report and evaluate performance.
This paper describes the evaluation of such a measure – daily discharge rate (DDR) – applied to the General Internal Medicine (GIM) service of the Toronto General Hospital for two consecutive years.
6.2 RATIONALE FOR MONITORING DAILY DISCHARGE RATE

Discharge represents an important efficiency bottleneck

Discharge of inpatients has emerged as a key efficiency bottleneck within hospital operations (Shepperd et al., 2004; Connolly et al., 2009). As the last process in the inpatient care pathway, delays and variation in discharge are known to have significant repercussions to upstream processes like emergency department patient flow and elective surgery scheduling/cancellations (Black and Pearson, 2002). One study found that delays in discharge accounted for nearly 2% of all inpatient days, so the costs incurred by delayed discharges are potentially significant (Godden et al., 2009). Therefore, developing tools to measure and monitor discharge efficiency is imperative.

Average length of stay inadequately measures discharge efficiency

Quantifying delays in discharge is one way to evaluate the efficiency of the discharge process. Delays are commonly quantified by measuring “unnecessary” length of stay - number of days where a patient’s clinical status was compatible with discharge but discharge did not occur (Carey et al., 2005). Additionally, discharge improvement initiatives are often evaluated by comparing pre- and post-intervention ALOS (Dainty and Elizabeth, 2009). However, there are significant limitations to reporting ALOS as an indicator of discharge efficiency.

First, ALOS measures the average period of time from hospital admission to discharge. It includes patient and social environment characteristics and hospital characteristics that may change over the course of the hospital stay. As a result, cause-and-effect relationships are more difficult to establish, verify and be held accountable for.
Next, ALOS measures past historical performance with an often substantial lag in reporting, making information less actionable. A more useful metric is expected length of stay (ELOS) - the LOS expected of a typical patient that account for various clinical characteristics (Canadian Institute for Health Information, 2009b). However, like ALOS, ELOS has operational factors embedded within its value which are not easily extracted from the calculation. As well, the work effort and patient volumes required to calculate hospital-specific ELOS are considerable.

Also, it is well-documented that day-of-the-week discharge trends exist and contribute to inefficient hospital discharge (Varnava et al., 2002; Wong et al., 2009). For example, reduced hospital staffing during weekends and limited weekend community capacity to accept referrals are cited as significant reasons why Saturday and Sunday are the least common days for discharge (Bell and Redelmeier, 2004; Canadian Institute for Health Information, 2009a). Unfortunately, analyzing ALOS by day of discharge can not readily detect these day-of-the-week trends since ALOS measures duration rather than counts.

In summary, length of stay, whether average or expected, provides hospitals with an aggregate measure of overall performance and is not intended for identifying and measuring discharge inefficiencies. New leading indicators that provide operational feedback on hospital efficiency are required.
6.3 Daily Discharge Rate – A New Indicator to Screen and Monitor Discharge Efficiency

We wanted a measure that directs attention towards inefficient discharge processes. DDR, as defined in Box 6.1, is simply the ratio of discharges to census, multiplied by 100. We designed DDR to specifically overcome the limitations posed by ALOS as a measure of discharge efficiency.

DDR measures shorter periods of time (time-span of one day) and therefore is more sensitive to operational factors. By definition, it addresses day-of-the-week trends explicitly. Figure 6.1 presents a box plot of ALOS and DDR values for the seven days of the week. Subset analyses (Wilcoxon Rank Sum Test) were performed between individual days of the week. Days with the same letter superscript are not significantly different while days with different letter superscripts are significantly different. For instance, ALOS on Monday, Tuesday, Wednesday and Friday were not significantly different from each other. Similarly, there were no significant differences among Tuesday, Wednesday and Thursday ALOS. However, both Saturday and Sunday ALOS showed a significant difference for each pairwise comparison (P < 0.05) (Figure 6.1A); for DDR, in addition to Saturday and Sunday, Friday showed a significant difference for each pairwise comparison (P < 0.05) (Figure 6.1B).
Box 6.1: What is daily discharge rate?

**Daily discharge rate** = \( \frac{\text{Number of discharges over a 24 hour period}^*}{\text{Total Census at the start of the 24 hour period}^#} \times 100\% \)

*To retain a focus on operational factors that can act as bottlenecks in discharge, *number of discharges over a 24 hour period* excludes discharges that are a result of either death or left against medical advice. These patients are however maintained in *total census at the start of the 24 hour period*.

#The 8AM today - 8AM tomorrow cycle best matches the decision-making and operations cycles of the inpatient and ED environments.
Figure 6.1: Box plot showing median levels of (a) average length of stay (ALOS) (b) daily discharge rate (DDR), by day of discharge (excludes left against medical advice and deaths) for the General Internal Medicine service, Toronto General Hospital from January 15th to December 15th for the two years, 2005 and 2006. Boxes show interquartile ranges, □ represent mean value, and I bars represent highest and lowest values not considered as outliers. Differences across the seven days of the week for ALOS and DDR were assessed by the non-parametric Kruskal-Wallis test followed by the Wilcoxon Rank Sum test for pairwise group comparisons. Medians with different letter superscripts are significantly different (P < 0.05). Statistical analysis was performed using SPSS (SPSS, Chicago, IL).
Capable as a sensitive screening tool

We have shown that DDR is sensitive to variation caused by day-of-the-week. It is also sensitive to other factors, including staff scheduling. Smooth and timely discharge requires the coordinated action of the entire clinical team, where any member can influence discharge. We have found a statistically significant decrease of nearly 50% in team DDR on Fridays where the team social worker is on vacation (9.4% with 95% CI, 5.3 to 13.6) to regular Fridays (18.4% with 95% CI, 15.9 to 20.9) (P = 0.02) (Galati M and Wu RC, unpublished data).

In the instance above, DDR had a direct and positive consequence on social work staffing within the GIM service. Specifically, in lieu of anticipated staff cutbacks, measuring and presenting DDR data to management, led to our GIM service retaining a social worker full-time equivalent per GIM team. In addition to retaining the necessary complement of social workers on weekdays, the GIM service is now staffed with a social worker on weekends to ensure continuity of care and help decrease variations in discharge caused by day-of-the-week.

Multiple disciplines including Nursing, Physiotherapy, Occupational Therapy, Respiratory Therapy, Pharmacy and other care providers can affect a patient’s status and care plan and therefore have potential to impact the discharge process. Each of these disciplines is an appropriate candidate for DDR analysis in relation to staffing levels, workload and bottlenecks in work tasks.
**Capable as an ongoing monitoring tool**

DDR must be presented in a real-time pragmatic manner in order to be an effective indicator capable of influencing clinician behaviour. Control charts are a form of graphical analysis designed to identify special-cause variation or out-of-control observations to prompt investigation or action (Tennant et al., 2007). Control charts include a plot of data over time with the calculated mean as the central horizontal line. When data points appear, without any unusual patterns within the control limits (±3 standard deviations from the mean), the process is said to be exhibiting common-cause variation and is considered to be in statistical control (Mohammed et al., 2008). There are several potential signals to identify special-cause variation within data points on a control chart (Guthrie et al., 2005).

Figure 6.2 shows control charts for ALOS and DDR on the GIM service over 48 consecutive Mondays. Each data point in the ALOS and DDR control charts represents the ALOS of patients and the percentage of 8AM census discharged (excluding deaths and left against medical advice) on that particular Monday for the GIM service, respectively.

For the ALOS control chart (Figure 6.2a), nearly all data points lie within the two-standard deviation warning limits. There are however two points of special-cause variation (May 16 and May 23). In both cases, further investigation revealed that the cause was associated with specific patients who had extremely long length-of-stays. For this reason, the ALOS was disproportionately high and caused the statistical outliers.
Figure 6.2: Control charts for average LOS (xmr-chart for continuous data) and daily discharge rate (p-chart for percentage data with varying denominator), on consecutive Mondays from January 15, 2005 – December 15, 2005 for the General Internal Medicine service, Toronto General Hospital. Upper and lower warning limits (UWL, LWL) are set at ±2 standard deviations from the mean; upper and lower control limits (UCL, LCL) are set at ±3 standard deviations. In the case where the lower control limit is below 0, limits are reset to 0.
Since ALOS is highly sensitive to cases with extreme large and small values, the averaged value may be misleading (Murphy and Noetscher, 1999). Plotting median LOS may be an alternative approach.

For DDR, the warning and control limits are stepped because they reflect the changes in the census between consecutive Mondays. DDR appears to be a more sensitive metric for detecting an “out of control” process (Figure 6.2b). DDRs were higher than expected in consecutive Mondays between Aug 8 and Sep 26 (dotted box identifying eight consecutive points above the mean and dotted circle identifying two of three consecutive points between a warning limit and a control limit). Also, three of the four points that lie below the lower warning limit correspond to statutory holidays (Victoria Day, Civic Holiday and Thanksgiving). As “out of control” DDR observations are identified, this may trigger Pareto analyses or fishbone diagrams to closely look at the constraints of those particular days and identify the most frequent reasons for delayed discharges. For example, ‘non-medical’ factors, including temporary reductions in diagnostic and interventional capacity or patients occupying beds waiting for a more appropriate community care setting to become available may be found to be significant discharge bottlenecks.

Valid relationship with average length of stay

In order for DDR to be considered an indicator of efficiency, it should demonstrate a valid and reliable relationship with other efficiency indicators, like ALOS.
Figure 6.3 illustrates the correlation between DDR and ALOS for the four clinical teams that provided patient care on the GIM service during the study period. Each coordinate represents the team ALOS and DDR for a 6-month period. In general as expected, as ALOS increased, DDR decreased. Also, over the 2-year period, Team B had the shortest ALOS and correspondingly highest DDR of all the teams while Team A had the longest ALOS and lowest DDR.

To illustrate the practical implications of DDR, we provide four examples that describe how DDR can be used in day-to-day operations (Box 6.2).
Figure 6.3: Daily discharge rate versus average LOS. Each point represents a 6-month team-specific average for clinical teams of the General Internal Medicine service, Toronto General Hospital, from January 15th to December 15th for the two years, 2005 and 2006.
Box 6.2: Day-to-day applications of daily discharge rate

Problem:
The hospital CEO has asked that all wards aim for a 15% reduction in length of stay. The current average length of stay is 8.1 days and a 15% reduction equals a target length of stay of 6.9 days. Since length of stay is a lagging indicator that can only be calculated after discharge, achieving this goal requires determining the expected length of stay (expected length of stay takes into account the reason for hospitalization, age, co-morbidity and complications) of each patient and then reducing it by 15%. Unfortunately, the work effort involved in determining individual expected lengths of stay is not reasonable for day-to-day operations. Without access to accurate and real-time information, the likelihood that the CEO and clinical teams will achieve their target length of stay is low.

Example 1: DDR is an actionable indicator
Solution
The linear regression analysis in Figure 3 states that each additional patient day is associated with a 0.8241 decrease in daily discharge rate. To decrease length of stay from 8.1 days to 6.9 days requires an increase in daily discharge rate from 9.9% to 11.0%. For an 8AM ward census of 100 patients, this translates to a working target of discharging 11.6 patients each day. With this calculated value, teams have a goal to work towards and a value to compare their outcomes against.

Example 2: DDR is generated in real time
Solution
While it may not be medically feasible to discharge 11.6 patients every day to achieve the 15% reduction in length of stay as desired by the hospital CEO, daily discharge rate presented in a control chart provides additional useful real-time operational information. Daily discharge rate can be measured every day for every team on every ward with minimal effort. Teams have a record of their performance, whether in the past 48 hours, week or month. This real-time feature allows for rapid course correction. For example, prior to morning rounds, the Unit Manager determines from the control chart that the range of discharges required to maintain within the warning limits based on that morning’s 8AM census of 100 patients is between 4.9 and 17.5 patients. Armed with this useful information, discharge discussions during rounds have greater potential to translate from discussion to corrective action. As a result, there is far greater potential to achieving the target length of stay.

Example 3: DDR drives better accountability within clinical teams
Solution
Achieving gains in efficiency is highly dependent on clinical team engagement. Within the hospital, Dr. X’s clinical team is the most efficient. Suppose on the first day of Dr. X’s rotation, he discharges Mr. F who has been in hospital for 100 days as a very complex case. Although Dr. X has only taken care of Mr. F for 1 day, Mr. F’s length of stay is assigned entirely to Dr. X (attending physician), positively skewing Dr. X’s average length of stay calculation for his patients and giving the CEO the impression that Dr. X is a low-performer. In contrast, daily discharge rate is unambiguously assigned to a clinical team or physician. Daily discharge rate, by definition, attributes equal weight to all of Dr. X’s patients, including Mr. F. Since length of stay inappropriately allocates the lack of efficiency to Dr. X’s team, it is very difficult for physicians and clinical teams to accept length of stay as a measure of efficiency. On the other hand, since daily discharge rate is a leading, real-time, fair and transparent measure, clinicians may feel more comfortable with applying it as an indicator of efficiency. As buy-in increases, there is likely a corresponding increase in probability that the hospital CEO and its clinical teams can achieve their goal in reducing length of stay.

Example 4: DDR is a sensitive screening tool able to capture system interventions
Solution
The VP of Patient Services is trying to create system-level improvements in patient flow across the hospital to help realize the CEO’s goal in reducing length of stay. She chooses to focus on daily discharge rate since it is sensitive to daily fluctuations in operations. She analyzes variations in daily discharge rate and finds that during weekends and long-weekends, there is a significant reduction in daily discharge rate. Upon further analyses, it is determined that radiology services are closed during these times. Daily discharge rate has prompted the identification of the system-level problem and now the VP is in a better position to make rational organizational decisions. Instead of maintaining the current state of operations, she decides to trial having radiology services open during weekends and will continue to monitor daily discharge rate to determine the cost-effectiveness of this intervention.
6.4 CAVEATS FOR FRONTLINE MANAGERS CONSIDERING MEASURING DAILY DISCHARGE RATE

One of many measures in the toolkit of metrics to evaluate care

DDR is designed to be used in conjunction with other indicators. This includes efficiency (e.g. ALOS, cost per weighted case), quality (e.g. readmission rates, percent of patients receiving appropriate venous thromboprophylaxis, percentage of completed discharge summaries), safety (e.g. adverse drug events, hospital-acquired infections, inpatient falls), and patient and staff satisfaction. Concurrent measurement will ensure DDR does not come at the expense of other measures (Laine et al., 2005).

Variation as opposed to an absolute number

The potential for inappropriate use of daily discharge as an absolute target, rather than an indicator of trends exists. We stress that DDR’s merit is based mostly on variation as opposed to an absolute number. The goal is not necessarily to reduce variability but to better understand variation to encourage the appropriate and efficient use of resources. When DDRs are low or high, due to some operational factor, there is likely inefficiency.

Since DDR is a ratio, the denominator (8AM census) can have a substantial impact on its value. When used as a metric to monitor variation via control charts, the census’ impact is taken into account as the warning and control limits vary depending on the calculated value. We caution the use of DDR as an absolute number to compare individual clinical teams, different inpatient wards, or institutions. Instead, in these
Settings, it should be used to monitor performance in terms of variation and sustained trends.

Validation of daily discharge rate

We need to further confirm the appropriateness of DDR as a performance metric of operational efficiency, further understand its strengths and limitations, and evaluate its generalizability. We have applied DDR in General Internal Medicine, a service that admits mostly elderly patients with a broad range of diagnoses and provides complex, labour-intensive care. Measuring DDR for other areas of the hospital like Cardiology, Neurology, and General Surgery that have different clinical and patient characteristics, and at multiple teaching and community hospitals is needed in order to have a valid measure of hospital operations that affects the entire spectrum of inpatient hospital care.
6.5 CONCLUSION

Daily discharge rate is a real-time, sensitive and actionable indicator of discharge efficiency. It is granular enough to effectively measure performance at the operational level and correlates well with ALOS. One of the key features of DDR is that it can be easily measured and reported on a daily basis. Via control charts, clinical teams can monitor, evaluate, and characterize delays by responding to variations in their DDR. Measurement and reporting of DDR allows for greater frontline staff accountability and substantially speeds and strengthens feedback of issues that impact discharge efficiency.

We believe DDR has the potential to drive timely improvements in the discharge process and ultimately improve the quality of care provided. It warrants consideration and further study by others interested in improving hospital operational efficiency.
CHAPTER 7

SUMMARY

The purpose of this chapter is to:

1. State the implications of this thesis, including the value of hospital operational data for comprehensive systems planning; the contribution of qualitative and quantitative modelling elements of system dynamics to hospital strategy; and the value of measuring daily discharge rate to focus improvement in operational efficiency.

2. Outline directions for future research in order to make thesis findings more generalizable.

7.1 IMPLICATIONS

While some findings within this thesis may not be generalizable to other institutions, to the extent that most hospitals are running near capacity, the methods used in this thesis can be applied by others faced with similar challenges. One message from this thesis is that there is value in using hospital operational data for comprehensive systems planning. Via administrative database analyses, we found that certain hospital operational processes as well as changes in specialty service admitting behaviour impacted ED congestion.

A second message from this thesis is that both qualitative and quantitative modelling elements of system dynamics have potential pragmatic contributions to hospital strategy and decision making. The process of rigorously extracting a conceptual
model of the ED-GIM problem from the mental models of clinician experts and hospital management clarified root problems and guided stakeholders toward courses of action. The empowerment of clinicians and hospital managers to move forward from a better understanding of the ED-GIM problem to taking action in redesigning upstream and downstream strategies to improve the situation is perhaps the most significant impact of this thesis.

- Building a conceptual model of the ED-GIM problem provided awareness to clinicians and hospital management of the interdependencies of their decisions and served as a roadmap for designing strategies to deal with the problem of ED boarders. Management recognized that GIM was inadequately serving as a safety net for acute patients presenting in the ED and was a significant source of ED congestion. Clinicians and medical directors have revised the Escalation Policy and ED Consultation Guidelines that describe which services patients will be admitted to, facilitating the realignment of patient volumes and redistribution of care across the hospital. Significant progress has been made at TGH in reducing ED boarders and boarding length of stay since implementation of the reformed policies in September 2008.

- Cancer Care Ontario (CCO) has been engaged in the data analysis that supports additional investment in resources for more complex, long term, and recurring inpatient care. Princess Margaret Hospital, another member hospital of UHN, introduced the REACH (Reducing Emergent and Acute Care Hospitalization) acute care clinic in May 2009 so that their oncology population could access emergent care within their facility as opposed to presenting at TGH ED. The
REACH clinic can initiate treatment and investigations earlier compared to a chronically backlogged TGH ED and their expertise and responsive care have proven beneficial to their patient population as well as in reducing the number of ED boarders at TGH.

- With quantitative decision support from a system dynamics computer simulation that demonstrated that smoothing discharges evenly across the days of the week reduced ED boarders, the GIM service moved forward with restructuring their clinical team admitting schedule from a ‘bolus’ system, where one team accepted all new admissions on a particular day, to a ‘drip’ system, where every team accepted a share of new admissions on a particular day. Evaluation of the new system is currently underway. The simulation model constructed is generalizable and can be extended to address other questions concerning the management of hospital capacity and estimates of future resource needs. Scenario tests performed suggested that improvements in ED performance can be achieved without additional resource investments (via smoothing discharges as opposed to increasing discharges).

A third message from this thesis is that daily discharge rate is a novel real time metric of hospital discharge efficiency sensitive to detect variations in operational factors that affect discharge.

- For example, in lieu of anticipated staff cutbacks, measuring daily discharge rate had a direct and positive consequence on the GIM service. In fact, GIM was able to retain a social worker full time equivalent per GIM team when data analyses
proved that daily discharge rates were nearly 50% lower on days where social workers were short-staffed. What’s more, in addition to retaining the necessary complement of social workers on weekdays, the GIM service is now staffed with a social worker on weekends to ensure continuity of care and help decrease variations in discharge caused by day of the week.

- Daily discharge rate is a key frontline efficiency metric in a proposed team-based scorecard to evaluate and report performance to GIM clinical care groups. The team-based scorecard is the initial step in creating a foundation for future initiatives to enhance the quality of care through performance-based incentives. The score card will measure frontline metrics in four relevant domains of patient care: patient satisfaction, quality of care, efficiency and inter-professional team health.

More generally, a clear message from this thesis is that the ‘ED-GIM’ problem is neither an ED nor a GIM problem, per se. GIM boarders in the ED are a symptom of a hospital-wide problem that is highly influenced by government level and hospital strategic decision making. While the ‘ED-GIM’ problem is a misnomer, General Internal Medicine, a service that admits mostly elderly patients with a broad range of diagnoses and provides complex, labour-intensive care is the ‘canary in the coal mine’. GIM is in a unique position to serve as a sensitive sensor to detect and measure changes that affect the entire spectrum of hospital care.
7.2 FUTURE RESEARCH

A common criticism received from publication of parts of this thesis in peer-reviewed journals is that the studies are limited to data from one institution. To make our findings more generalizable, these questions need to be addressed in other inpatient services of other institutions in a city, a region or a country. Using comparative data from a similar teaching institution would be a good first step.

In Chapter 2, we described recent emergent inpatient admitting trends and established that GIM served as a safety net for specialty services. Further study is required to determine whether GIM serves a similar role in community hospitals and the impact of physician admitting behaviour in these community settings.

In Chapter 3, we evaluated hospital operational factors that affect daily discharge rate. Further study is required to investigate whether admission and rotation schedules impact daily discharge rates of community hospitals as well.

In Chapter 4, we developed a system dynamics computer simulation used to show that increased weekend discharges would decrease the number of GIM patients boarding in the ED. The findings present challenges to health services. Exploring what trying to achieve this would mean for service organization and delivery would help managers decide feasibility. Additionally, the model should be tested on other hospital datasets.

In Chapter 5, we designed a conceptual model of the ED-GIM problem using system dynamics methodology with the aim of creating a generalizable roadmap to sustainable improvements in ED congestion. Further study is required to investigate the impact of incentive structures for emergent and elective care on complicated hospital systems.
In Chapter 6, daily discharge rate is introduced as a real-time and actionable indicator of operational efficiency. Applying daily discharge rate to other inpatient services like Cardiology, Neurology, and General Surgery is required to confirm the appropriateness of discharge rate as a performance metric of operational efficiency.
Figure A1: Stock-flow diagram of the system dynamics simulation model constructed to evaluate smoothing of discharges over the course of the week.
MODEL EQUATIONS

"Transfer out of ED (O)" = DELAY FIXED ( Status of ANB*Sum Unit DC*Admission Fraction Other, Bed TAT, 0) 
~ patients/hour 
~ rate at which GIM "Other" pts are transferred to ward bed 

Status of ANB= IF THEN ELSE(GIM Admit No Bed in ED<=0, 0 , 1 ) 
~ Dmnl 
~ Outputs 1 if Admit No Bed stock is not empty; 0 if otherwise 

"Transfer out of ED (I)" = DELAY FIXED ( Status of ANB*Sum Unit DC*Admission Fraction Inter, Bed TAT, 0) 
~ patients/hour 
~ rate at which GIM "Inter" pts are transferred to ward bed 

"Transfer out of ED (H)" = DELAY FIXED ( Status of ANB*Sum Unit DC*Admission Fraction Home, Bed TAT, 0) 
~ patients/hour 
~ rate at which GIM "Home" pts are transferred to ward bed 

"Bed TAT Sat-Sun"= 7.48449 
~ hour 
~ historical weekend average 

day of wk= MODULO(day of unit year, 7) 
~ day 
~ range: Sunday (0),...,Saturday (6) 

DC ED Patients= "Mon-Fri?"*(0.70073+0.11409*"ANB @8AM")+"Sat?"*1.69231+"Sun?"*1.65 
~ patients 
~ number of GIM pts discharged from ED per day
Sum Daily Unit Home DC=
  Discharge Home*24
  ~ patients/day
  ~ number of GIM pts discharged home per day

Sum Daily FB=
  ("Transfer out of ED (H)"+"Transfer out of ED (I)"+"Transfer out of ED (O)")*24
  ~ patients/day
  ~ number of GIM pts transferred out of the ED to ward per day

Sum Daily Unit Inter DC=
  Discharge Inter*24
  ~ patients/day
  ~ number of GIM pts discharged to inter-facility per day

Bed TAT=
  "Bed TAT M-F"*"Mon-Fri?"+"Bed TAT Sat-Sun"*"Sat-Sun?"
  ~ hour
  ~ Daily bed turn-around time

Discharge Fraction Home=
  "Sun?"*0.0426476+"Mon-Thurs?"*WC+"Fri?"*0.205641+"Sat?"*0.0745096
  ~ Dmnl
  ~ Proportion of GIM home stock @ 8AM discharged by day of week

"Sat-Sun?"=
  IF THEN ELSE(day of wk=0 :OR: day of wk=6, 1 , 0)
  ~ Dmnl
  ~ outputs 1 if weekend

"Mon-Fri?"=
  IF THEN ELSE(day of wk>=1 :AND: day of wk<=5, 1 , 0)
  ~ Dmnl
  ~ outputs 1 if weekday

Discharge From ED=
  IF THEN ELSE("ANB @8AM"<=3, 0 , DC ED Patients*Hourly Discharge from ED Trend)
~ patients/hour
~ rate at which gim pts in the ed are discharged from ed. historically, when gim pts in the ed <=3, on average, 0 pts discharged from ed

"Bed TAT M-F"=
5.78044+0.18457*Sum Daily Unit DC
~ hour
~ weekday average bed turn-around time

"ANB @8AM"=SAMPLE IF TRUE(
hr of unit day=0,GIM Admit No Bed in ED,GIM Admit No Bed in ED)
~ patients
~ determines the level of the GIM in ED stock at 8AM

Hourly Discharge from ED Trend= WITH LOOKUP (hr of unit day, 
{(0,0)-
(24,0.2),(0,0.00495049),(1,0.0148515),(2,0.029703),(3,0.0445545),(4,0.0643564),
(5,0.0841584),(6,0.0792079),(7,0.101485),(8,0.141089),(9,0.116337),(10,0.126238),
(11,0.0371287),(12,0.0618812),(13,0.0272277),(14,0.0123762),(15,0.00247525),
(16,0.00990099),
(17,0.0148515),(18,0.00742574),(19,0.00495049),(20,0.00247525),(21,0.00495049),
(22,0.00247525),(23,0.00495049) ))
~/hour
~ historical hourly proportion of gim discharges from ed

"Total GIM Census @8AM"=
"ANB @8AM"+"Total GIM Unit Census @8AM"
~ patients
~ sum of ed and unit stocks at 8AM

Daily Discharge From ED=
Discharge From ED*24
~ patients/day
~ number of pts discharged from ed per day
Sum Daily Unit DC =
   Sum Unit DC*24
   ~ patients/day
   ~ number of pts discharged from unit per day

Discharge Fraction Inter = WITH LOOKUP ( 
   day of wk,
   ((0,0)-
   (7,0.1]), (0,0.00414886), (1,0.0762089), (2,0.0874086), (3,0.0844419), (4,0.0898),
   ),(5,0.0917993),(6,0.0227773 ))
   ~ Dmnl
   ~ Proportion of GIM inter stock @ 8AM discharged by day of week

Hourly Discharge Home Trend = WITH LOOKUP ( 
   hr of unit day,
   ((0,0)-
   (24,0.2]), (0,0.00536193), (1,0.0080429), (2,0.0227882), (3,0.0536193), (4,0.0723861)\n   ),(5,0.100536), (6,0.11059), (7,0.126005), (8,0.121314), (9,0.11193), (10,0.136059), (11,\n   0.0743968), (12,0.0241287), (13,0.00938338), (14,0.0080429), (15,0.00603217), (16,\n   0.00335121)\n   ),(17,0.00134048), (18,0.000670241), (19,0.000670241), (20,0.00201072), (21,0), (2\n   2,0.000670241)\n   ),(23,0.000670241 ))
   ~ /hour
   ~ historical hourly proportion of gim home discharges

Hourly Discharge Inter Trend = WITH LOOKUP ( 
   hr of unit day,
   ((0,0)-
   (24,0.2]), (0,0.0867052), (1,0.0895954), (2,0.083815), (3,0.101156), (4,0.0924855)\n   ),(5,0.118497), (6,0.0953757), (7,0.0751445), (8,0.0751445), (9,0.066474), (10,0.043\n   3526)\n   ),(11,0.0231214), (12,0.0115607), (13,0.00867052), (14,0.00578035), (15,0.00289017), (16)
Historical hourly proportion of gim inter discharges:

Hourly Discharge Other Trend = WITH LOOKUP (hr of unit day, 
[(0,0), (1,0.0179104), (2,0.0268657), (3,0.0626866), (4,0.0567164)]

Discharge Other = "Other @8AM" * Discharge Fraction Other * Hourly Discharge Other Trend

"Fri?" = IF THEN ELSE(day of wk=5, 1, 0)

"Mon-Thurs?" = IF THEN ELSE(day of wk>=1: AND: day of wk<=4, 1, 0)

"Sat?" = IF THEN ELSE(day of wk=6, 1, 0)
~ Dmnl
~ outputs 1 if saturday

Discharge Fraction Other = WITH LOOKUP (day of wk, 
  ([(0,0)-
    (7,0.2)],(0,0.07418),(1,0.101741),(2,0.141307),(3,0.112208),(4,0.134702),(5,
    0.114774),(6,0.0800903) ))
~ Dmnl
~ Proportion of GI M other stock @ 8AM discharged by day of week

Discharge Inter =
  "Inter @8AM"*Discharge Fraction Inter*Hourly Discharge Inter Trend
~ patients/hour
~ rate at which gim pts are discharged inter

Discharge Home =
  "Home @8AM"*Discharge Fraction Home*Hourly Discharge Home Trend
~ patients/hour
~ rate at which gim pts are discharged home

"Sun?" =
  IF THEN ELSE(day of wk=0, 1 , 0)
~ Dmnl
~ outputs 1 if sunday

Admission Fraction = WITH LOOKUP (day of wk, 
  ([(0,0)-
    (10,0.15)],(0,0.0878211),(1,0.0849794),(2,0.0977754),(3,0.103463),(4,0.0967614\ 
    ),(5,0.0918004),(6,0.0982228) ))
~ Dmnl
~ proportion of ed visits admitted to gim by day of week

Admission Fraction Home =
  0.710904
~ Dmnl
~ historical proportion of gim home pts
Admission Fraction Inter = 
  0.144354
  ~ Dmnl
  ~ historical proportion of gim inter pts

Admission Fraction Other = 
  0.144742
  ~ Dmnl
  ~ historical proportion of gim other (die, lama, intra) pts

ALC Fraction = 
  "Inter @8AM"/"Total GIM Unit Census @8AM"
  ~ Dmnl
  ~ proportion of unit census at 8AM that is inter

Hourly Admission Trend = WITH LOOKUP ( 
  hr of unit day, 
  ([0,0)-
  (24,0.1)],(0,0.0248351),(1,0.0271634),(2,0.0287156),(3,0.0353124),(4,0.0232829)
  ,5,0.0263873),(6,0.0205665),(7,0.0318199),(8,0.0294917),(9,0.032208),(10,0.03
  06558
  ,11,0.0213426),(12,0.0477299),(13,0.0415212),(14,0.0395809),(15,0.064416),(1
  6,0.072953
  ,17,0.0698487),(18,0.0799379),(19,0.0616997),(20,0.0698487),(21,0.064416),(22
  ,0.0492821
  ,(23,0.00698487) ))
  ~ /hour
  ~ proportion of ed visits admitted to gim by hour of day

"Home @8AM"=SAMPLE IF TRUE( 
  hr of unit day=0,Home,Home)
  ~ patients
  ~ determines the level of the GIM home stock at 8AM

"Inter @8AM"=SAMPLE IF TRUE( 
  hr of unit day=0,Inter,Inter)
  ~ patients
  ~ determines the level of the GIM inter stock at 8AM
"Other @8AM"=SAMPLE IF TRUE(  
  hr of unit day=0,Other,Other)  
~ patients  
~ determines the level of the GIM other stock at 8AM

"Total GIM Unit Census @8AM"=  
"Home @8AM"+"Inter @8AM"+"Other @8AM"  
~ patients  
~ sum of home, inter and other stocks at 8AM

GIM Admission Rate=  
  Day of wk ED visits*Admission Fraction*Hourly Admission Trend  
~ patients/hour  
~ rate of inpatient admission to gim

WC=  
  0.21243+((-0.23133)*ALC Fraction)  
~ Dmnl  
~ linear function of ALC fraction

day=  
  INTEGER(Time/24)  
~ day  
~ range: day0,...,day end of simulation

hr of unit day=  
  INTEGER(MODULO(Time, 24))  
~ hour  
~ range: hour0,...,hour23

Day of wk ED visits= WITH LOOKUP (  
  day of wk,  
  ([(0,60)-
  (10,90)],(0,68.4792),(1,78.5),(2,76.3333),(3,73.0833),(4,74.9792),(5,77.8085|
  ),(6,69.5833) )
~ patients  
~ historical daily number of ed visits by day of week
day of unit year=
    MODULO(day,364)
    ~ day
    ~ range: day0,...,day364

GIM Admit No Bed in ED= INTEG (  
    +GIM Admission Rate-Discharge From ED-"Transfer out of ED (H)"-"Transfer out of ED (I)"
    -"Transfer out of ED (O)",  
    13)
    ~ patients
    ~ stock of gim pts in ed

Home= INTEG (  
    +"Transfer out of ED (H)"-Discharge Home,  
    28)
    ~ patients
    ~ stock of gim home pts on unit

Inter= INTEG (  
    +"Transfer out of ED (I)"-Discharge Inter,  
    13)
    ~ patients
    ~ stock of gim inter pts on unit

Other= INTEG (  
    +"Transfer out of ED (O)"-Discharge Other,  
    5)
    ~ patients
    ~ stock of gim other pts on unit

Sum Unit DC=  
    Discharge Home+Discharge Inter+Discharge Other
    ~ patients/hour
    ~ sum unit discharges (home, inter, other)

********************************************************
-Control
********************************************************~
Simulation Control Parameters

| FINAL TIME  = 4368 Hour |
| ~ The final time for the simulation. |

| INITIAL TIME  = 0 Hour |
| ~ The initial time for the simulation. |

| SAVEPER = TIME STEP Hour [0,?] |
| ~ The frequency with which output is stored. |

| TIME STEP  = 0.03125 Hour [0,?] |
| ~ The time step for the simulation. |
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