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Transforming Hospital Emergency Department Workflow and Patient Care

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THE FRANZ EDELMAN AWARD
Achievement in Operations Research

Transforming Hospital Emergency Department Workflow and Patient Care

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When we encounter an unexpected critical health problem, a hospital's emergency department (ED) becomes our vital medical resource. Improving an ED's timeliness of care, quality of care, and operational efficiency while reducing avoidable readmissions, is fraught with difficulties, which arise from complexity and uncertainty. In this paper, we describe an ED decision support system that couples machine learning, simulation, and optimization to address these improvement goals. The system allows healthcare administrators to globally optimize workflow, taking into account the uncertainties of incoming patient injuries and diseases and their associated care, thereby significantly reducing patient length of stay. This is achieved without changing physical layout, focusing instead on process consolidation, operations tracking, and staffing. First implemented at Grady Memorial Hospital in Atlanta, Georgia, the system helped reduce length of stay at Grady by roughly 33 percent. By repurposing existing resources, the hospital established a clinical decision unit that resulted in a 28 percent reduction in ED readmissions. Insights gained from the implementation also led to an investment in a walk-in center that eliminated more than 32 percent of the nonurgent-care cases from the ED. As a result of these improvements, the hospital enhanced its financial standing and achieved its target goal of an average ED length of stay of close to seven hours. ED and trauma efficiencies improved throughput by over 16 percent and reduced the number of patients who left without being seen by more than 30 percent. The annual revenue realized plus savings generated are approximately $190 million, a large amount relative to the hospital's $1.5 billion annual economic impact. The underlying model, which we generalized, has been tested and implemented successfully at 10 other EDs and in other hospital units. The system offers significant advantages in that it permits a comprehensive analysis of the entire patient flow from registration to discharge, enables a decision maker to understand the complexities and interdependencies of individual steps in the process sequence, and ultimately allows the users to perform system optimization.

Keywords: systems transformation; systems optimization; machine learning; multiple-resource allocation; mixed-integer program; simulation; decision support; emergency department; acuity level; length of stay; readmission; operations efficiency.

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Over the past two decades, emergency department (ED) crowding and delays have become serious issues for hospitals and health systems in the United States. ED visits have increased by more than 2 million per year, characterized by patients who were older and sicker, and thus required more complex, time-consuming workups (i.e., complete medical examinations, including medical history, physical exam, laboratory tests, X-rays, and analysis) and treatments, and by nonurgent patients who use the ED in place of primary care facilities. The National Hospital Ambulatory Medical Care survey (Centers for Disease Control 2010) reported 130 million ED visits in 2010. Despite increased demand, 19 hospitals closed in 2011. In 2012, hospitals reported that more than 40 percent of ED patient visits were for nonurgent care, contributing to long waiting times, decreased quality and timeliness of care, and decreased patient satisfaction. Numerous reports have questioned the ability of U.S. EDs to handle this increasing demand for emergency services (Richardson and Hwang 2001; Lewin Group 2002; Derlet 2002; Derlet et al. 2001; Derlet and Richards 2000, 2002; Taylor 2001).

Our project showcases the transformation that can happen when operations research (OR) is applied to improve a hospital's ED operations. Working with Grady Memorial Hospital (also referred to as Grady Hospital or Grady), our operations researchers devised a customizable model and decision support system that couples machine learning, simulation, and optimization to help hospitals improve effectiveness in their EDs. Part of the Grady Health System, Grady Hospital is the fifth-largest safety net hospital in the United States; these hospitals provide a disproportionate amount of care to vulnerable populations (United States Department of Health and Human Services 2014). Grady implemented our decision support system with beneficial results, such as reduced length of stay (LOS), patient waiting times, and readmissions (i.e., repeat admissions related to an initial admission), and improved efficiencies and throughput, all without investing additional funds or resources. Subsequently, 10 other hospitals implemented our system and also achieved beneficial results.

Grady's ED, which is a Level I trauma center, operates the country's largest hospital-based ambulance service. Its ED receives more than 125,000 patient visits per year, more than 20,000 of whom are trauma patients. Grady provides critical services to Georgia's health system. It is home to Georgia's only poison control center, the area's first primary stroke center, and Georgia's first cancer center for excellence. Its extended trauma facilities include surgical suites, burn units, the LifeFlight and AngelFlight air medical transport programs, Angel II neonatal transport units, and an emergency medical service ambulance program.

Grady serves a large population of uninsured patients and diverse socioeconomic groups. Of more than 621,000 annual patient visits, only eight percent of these patients are privately insured (versus 50 percent nationally). In 2007, Grady "was in desperate need of more than $200 million to remain solvent. Grady's financial collapse has serious consequences not just for metro Atlanta—its crisis could reverberate across the state … Experts say its inefficient customer service and general administration have created this financial crisis of epic proportions" (de Moura 2007). In the midst of this financial crisis, a new management team came on board to rescue the hospital and transform its operations. The new leadership was committed to serious ED system transformation and initiated a joint collaboration with our team of operations researchers. Through extensive data collection and vigorous OR analytical advances and recommendations, Grady adopted the transformative steps, which included addressing readmissions, quality, and efficiency of care before the Affordable Care Act and its associated penalties were put in place.

The ED crisis is being experienced across the nation. In January 2014, the American College of Emergency Physicians ranked [nationwide] ED access as D+ to reflect "that hospitals are not getting the necessary support in order to provide effective and efficient emergency care" (American College of Emergency Physicians 2014). Grady feels a more-than-average burden; it treats all patients, regardless if they have insurance. For each service that it provides, it incurs costs for which it will be reimbursed only a small portion. In addition, many critically ill patients (including referrals from other EDs) are routed to Grady because of the excellent specialty care that it provides.

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The novelty of our OR work has five main aspects. To the best of our knowledge, these have not been incorporated in previous methods or studies:

1. We optimize within the ED system simulation, rather than relying on a scenario-based method, so that the results more closely approach global optimization. The global solution involves aligning and consolidating operations, optimizing staffing, and optimizing processes.
2. We dynamically and stochastically incorporate treatment patterns and patient characteristics within an agent-based simulation, while focusing on ED operations and quality improvement.
3. We model ED readmissions using data that simultaneously encompass demographics, socioeconomic status, clinical information, hospital operations, and disease behavioral patterns.
4. We explicitly model the interdependencies to and from the ED with numerous other hospital departments, capturing inefficiencies in those processes.
5. We integrate machine learning within the simulation-optimization framework.

We also note that in our work, all medical terms and related metrics are defined as is customary in the medical community.

From a hospital's perspective, healthcare leaders have acknowledged that this work advances ED operations in several ways, which we describe in the *Benefits and Impacts* section. From an OR perspective, the collaboration this project engendered and the challenges it presented have led to both theoretical and computational advances in optimization and simulation.

Background

Crowded ED conditions have sparked research on several fronts. Eitel et al. (2010) discussed different methods for improving ED quality and flow, including demand management, critical pathways, process mapping, emergency severity-index triage, bedside registration, and Lean and Six Sigma management methods (Bahensky et al. 2005). Popovich et al. (2012) developed a volume-driven protocol and implemented it through the use of published evidence, which focused on essential endpoints of measurement. Wiler et al. (2010) evaluated interventions, such as immediate bedding, bedside registration, advanced triage, physician and (or) practitioner at triage, and dedicated fast-track service lines, all of which are considered potential solutions to streamline the front-end processing of ED patients. Ashby et al. (2008) optimized patient flow throughout the inpatient units, while modeling and observing the impacts on other interdependent parts of the hospital, such as the ED and operating rooms. Kolker (2008) tried to establish a quantitative relationship between ED performance characteristics, such as percentage of time on ambulance diversion and the number of patients in queue in the waiting room, and the upper limits of patient LOS. Moskop et al. (2009) identified and described operational and financial barriers to resolving the crisis of ED crowding; they also proposed a variety of institutional and public policy strategies to overcome those barriers. Nugus et al. (2011) used an ethnographic approach that involves direct observation of on-the-ground behaviors, observing interactions among physicians and nurses, emergency clinicians, and clinicians from other hospital departments to identify indicators of and responses to pressure in the day-to-day ED work environment. DeFlitch et al. (2007) reported provider-directed queuing for improving ED operations. McCarthy et al. (2009) used discrete-time survival analysis to determine the effects of crowding on ED waiting room, treatment, and boarding times (i.e., the time spent in the ED after the decision has been made to admit the patient to the hospital) across multiple sites and acuity levels. Sturm et al. (2010) identified predictors that can influence nonurgent pediatric ED utilization.

Challenges and Objectives

Although some of the ED advances have been successful, the improvement is often not sustainable, or it redirects inefficiencies from one area of the ED to another, or to other hospital divisions. Poor results from these approaches are partly because the requisite data are very time consuming to collect, often resulting in poor data being entered into a model. In addition, a model may be flawed if important elements and system dependencies are overlooked in its design.

Readmissions are a key challenge in ED performance. In particular, avoidable readmissions (i.e., readmissions resulting from an adverse event that

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occurred during the initial admission or from inappropriate care coordination following discharge) through the ED have become a major burden on the U.S. health system; see Minott (2008). Recent research shows that nearly one in five patients are readmitted to the discharging hospital within 30 days of discharge; these readmissions accounted for $17.8 billion in Medicare spending in 2004 (Osei-Anto et al. 2010).

Numerous studies have been conducted to identify frequently readmitted patients' characteristics and construct patient profiles to aid hospitals in predicting these patients. These studies have identified a number of demographic and clinical factors that are thought to significantly correlate with readmission. Other factors concerning hospital operations have also been investigated. Various statistical tools have been used to identify patient factors that are associated with readmissions (Allaudeen et al. 2011a, Billings et al. 2006, Hasan et al. 2010, Kirby et al. 2010). Westert et al. (2002) conducted an international study, including three U.S. states and three countries, to find patterns in the profiles of readmitted patients. The findings are divided into demographic and social factors, clinical factors (Billings et al. 2006, Southern et al. 2004), and hospital operations factors (Benbassat and Taragin 2000, Davidson et al. 2007, Joynt et al. 2011, Scuteri et al. 2011, VanSuch et al. 2006, Westert et al. 2002). A study of 26 readmission risk-prediction models concluded that after reviewing 7,843 citations, none of the models analyzed could suitably predict future hospital readmissions (Kansagara et al. 2011). Allaudeen et al. (2011b) noted that healthcare personnel could not accurately predict the readmission of patients discharged from their own hospitals; however, conclusions from these studies may be premature, given that much of the analyses were performed via logistic regression on only subsets of data. We recently published a readmission study in which, for the first time, a predictive model can incorporate comprehensive factors related to demographics and socioeconomic status, clinical and hospital resources, operations and utilization, and patient complaints and risk factors for global prediction (Lee et al. 2012a). Our approach empowers healthcare providers with good predictive capability, which we generalized for this Grady study.

The Affordable Care Act, its influence on Medicaid and Medicare payments, the high cost of emergency care, the persistent nonurgent visits, and the penalties imposed because of inappropriate readmissions and hospital-related health problems demand transformation of ED patient care and workflow.

This project focuses on large-scale systems modeling and decision analytics for modeling and optimizing the workflow for an ED. Specifically, we aim to improve workflow, reduce wait time, improve quality and timeliness of care, and reduce the number of avoidable readmissions. Although most studies incorporate simulation to model ED operations and perform scenario-based improvement (e.g., Medeiros et al. 2008), we believe that our model is the first to intertwine machine learning, simulation, and optimization into one system in which (1) the ED patient characteristics are analyzed and patterns uncovered, and (2) operations and workflow are modeled and resources optimized within the system to achieve the best performance outcome.

Grady began an ED process transformation with our OR team in 2008. At that time, the average patient LOS in its ED exceeded 10 hours. LOS represents the time between a patient's arrival at the ED and the time that patient is discharged from the ED or admitted to the hospital. Thus, LOS includes the door-to-provider time, the time the patient waits for the service and receives care, and the boarding time. Hence, LOS is often dominated by long stretches of nonservice times. Grady's goal was to achieve a LOS of close to seven hours and reduce its readmissions rate by 25 percent. We refer to the period from the beginning of the study in 2008 to the time of the sustained improved performance (July 2011) as Phase I. As a result of the Phase I improvements, the hospital was able to use sponsored funds to open a walk-in center for low-acuity patients, further driving down costs and LOS (Williams 2011). In addition, the implementation of an electronic medical record (EMR) system in October 2010 has enabled the administration to better track hospital operations. Because of the alternative care options and the addition of a new dedicated 15-bed trauma center, the dynamics of ED patient visits have changed. Phase II captures the period of ED advances from 2011 to the time of this writing. This paper summarizes the OR analytic, system-driven advances in the ED and

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their associated performance outcomes during these two phases. By design, the two phases overlap.

Methods and Design of Study

The study involves seven major steps, as follows:

1. Process mapping of ED patient and service workflow via structured interviews and objective process observations.
2. Time-motion studies of patient arrival, service processes, and analysis of hospital data.
3. Development of a machine-learning predictive analytic framework to process data and predict patient characteristics, complaint types, and admission and readmission patterns.
4. Development of a computerized simulation-optimization system.
5. System optimization and comparison of optimal system performance with existing operations.
6. Determination of actionable recommendations for implementation.
7. Evaluation of system improvements.

Figure 1 highlights the study schema and the interdependencies of our methods. The human-centered computational modeling environment comprises data analytics served by innovative OR predictive decision tools. We simultaneously explore patterns of patient behavior and care characteristics, provider decision and process workflow, facility layout design, and staffing, where resource allocation, cognitive human behavior, and care patterns are optimized globally for best outcomes, as measured by LOS and readmissions. Uncovering patterns in patient care helps to appropriately align resources with demands, and enables providers to better anticipate needs. Exploring facility design provides decision makers with the envisioned improvement before they embark on an expensive layout redesign effort.

ED Workflow and Services

Patients who visit the ED for care are evaluated first at the triage area to determine the severity of their injuries and (or) conditions. They are assigned an acuity level based on the emergency severity index (ESI), a five-level index for prioritizing ED patients for care, ranging from level 1 (emergent and requiring multiple resources) to level 5 (nonurgent and least resource intensive). The ESI is unique among triage tools, because it categorizes ED patients by both acuity and resource needs.

At Grady, the blue zone is used to treat high-acuity patients (levels 1 and 2) and all prisoners, except those with significant trauma. (Note that a detention area for prisoners is located inside the blue zone and

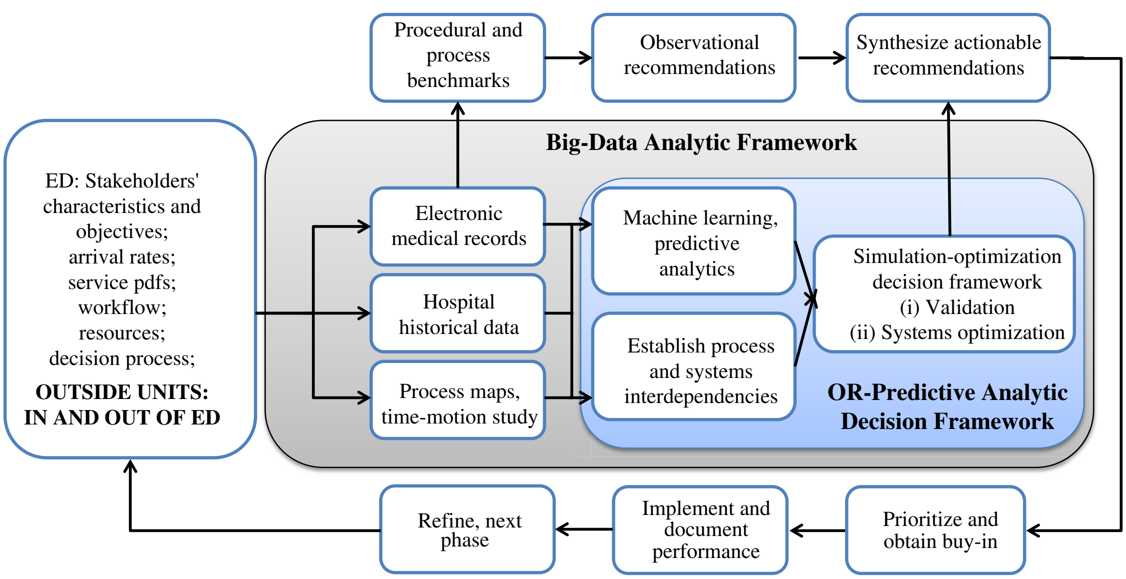

Figure 1: (Color online) This figure shows the study schema and interdependencies of the analytic framework that we use. These interdependencies are crucial to achieving a valid description of the actual processes.

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prisoner patients are registered in the blue-zone treatment area). A major resuscitation room anchors this area, which also includes eight critical care rooms, seven respiratory isolation rooms, and several general-patient-care areas. The red zone is used to treat general patients. This area has general-care rooms, an orthopedic room, a gynecology evaluation room, and an eye, ear, nose, and throat room. All rooms in the blue and red zones are capable of cardiac monitoring. In 2010, based on our Phase I results, Grady added a clinical decision unit. This unit provides an alternative to admission to the main hospital by providing observation services for those patients who have already received treatment in the ED. All patients in the clinical decision unit are evaluated by a case manager who helps coordinate care, provide education, and ensure appropriate follow-up. A patient who is not improving is sent to the hospital's main building for admission.

The mission of the patient ambulatory care express area (PACe) is to treat patients with relatively minor conditions. The PACe facility operates 24 hours a day, seven days a week, and is staffed primarily by nurse practitioners and physician assistants. The trauma center is designed to treat patients with trauma levels 1, 2, and 3, as categorized by the American Trauma Society (2014). Trauma operating rooms are staffed 24 hours a day year-round.

Patients arriving in an ambulance or other vehicle enter the ED through the ambulance arrival area, which is separate from the walk-in area. Here, patients determined to be ESI level 1 or 2 will be triaged and sent directly to the blue or red zone. Level 3 and 4 patients are triaged, sent to the ED waiting room, and enter the same queue as the patients in the walk-in area to wait for a bed in either zone. Walk-in patients, some of whom may not be assigned an acuity level, are treated by the walk-in triage physician and discharged from there.

Table 1 summarizes the ED patient care and resources, excluding the walk-in. Figures 2(a)–2(d) show the workflow process maps at the start of our study.

Data Collection and Time-Motion Studies

In this section, we discuss the two phases of our study.

Phase I. From August 2008 through February 2009, multiple trained observers collected ED data by reviewing files and charts and conducting interviews and time-motion studies related to services at various stations, as guided by the process maps. The data collected in this manner contain 45,983 data fields covering 2,509 patients. In addition, the hospital maintained vital statistics, including acuity level, LOS, and discharge data. Grady also provided readmission status for 42,456 patients. Furthermore, we received more than 40,000 individual service times for laboratory turnaround—the amount of time between the time a

		Space/beds		Worker type		
	Patient type	2008	2010	Attending physicians	Mid-level providers	Nurses
Triage	All			Yes	Nurse practitioners, physician assistants	Yes
Blue zone (acuity levels 1 and 2)	High-acuity patients and all prisoners without significant trauma	34	37	Yes	Residents	Yes
Red zone (acuity levels 2 and 3)	General patients	25	21	Yes	Residents	Yes
Clinical decision unit	Treated ED patients who need observation	0	7	Yes	No	Yes
PACe (acuity levels 4 and 5)	Patients with relatively minor conditions	8	8	No	Nurse practitioners, physician assistants	Yes
Trauma center	Patients who meet either trauma level 1, 2, 3 criteria in addition to any child involved in a traumatic accident, any patient arriving on a backboard, all gunshot and stab victims, and patients with complex extremity injuries or burns	4	15	Yes	Residents	Yes

Table 1: The table shows zones, patient and worker types, and resource availability.

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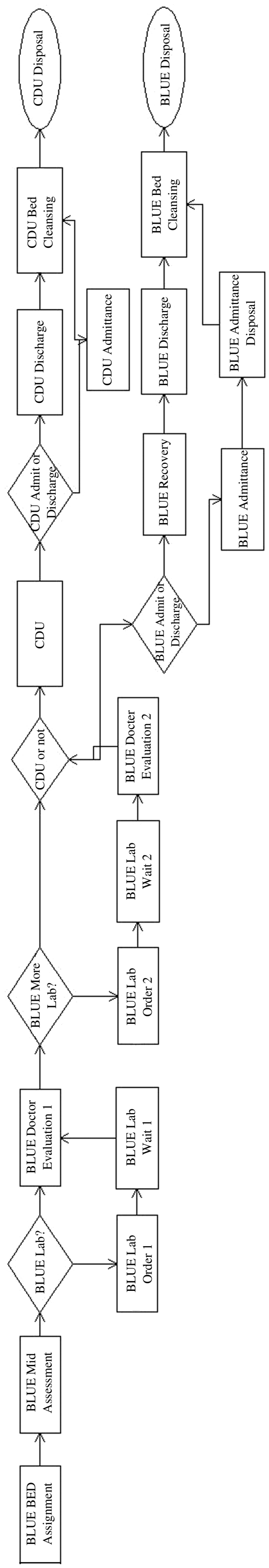

Figure 2(a): The flowchart shows the workflow process map for the blue zone.

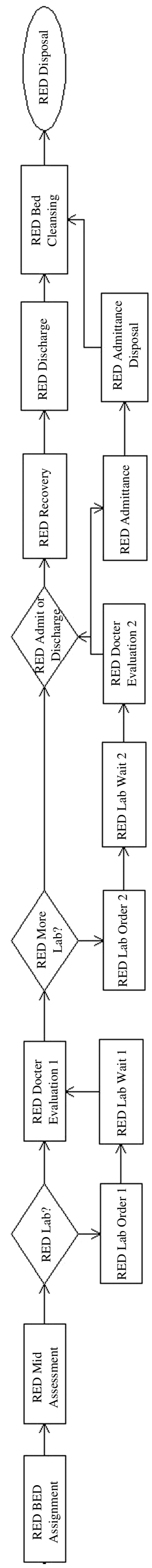

Figure 2(b): The flowchart shows the workflow process map for the red zone.

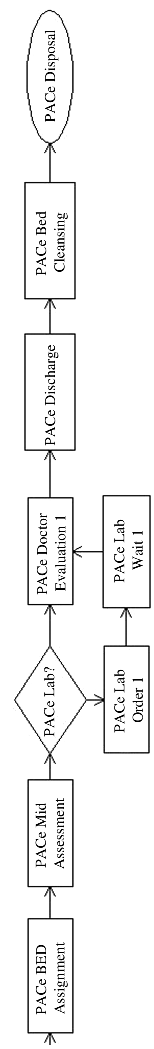

Figure 2(c): The flowchart shows the workflow process map for the PACe.

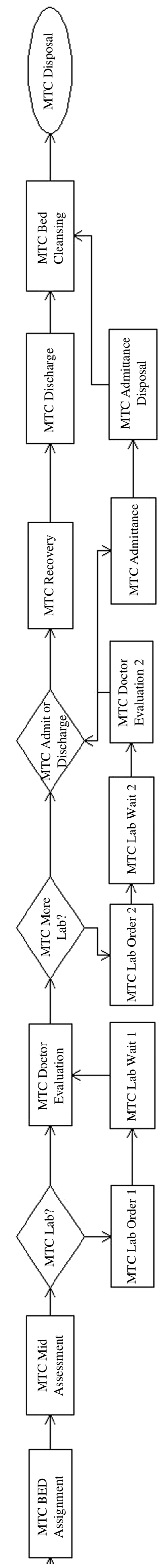

Figure 2(d): The flowchart shows the workflow process map for the trauma center.

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laboratory receives a specimen and the time the results are available.

Phase II. In Phase II, data from 16,217 patient visits from October 28, 2010 to December 31, 2010 were pulled from the EMR system. For each visit, data include patient information, ED admission time, hospital discharge time, acuity level, ED zones, diagnosis, and insurance type. The EMRs also include time stamps for relevant events, including registration, triage, laboratory orders and results, doctor assessment, observation, and discharge. We supplemented the EMR ED data with observations and time-motion studies at the triage and registration areas, and sampled treatment and wait times inside the rooms by shadowing various care providers.

By identifying the responsibilities of each type of worker via shadowing in the ED and reviewing the EMR system patient timeline, we found variability and randomness in arrival and treatment processes and workers' responsibilities. The variability emerges from the delivery practices of the nurses, mid-level practitioners, and attending physicians. Our model may not describe each case in the ED; however, it represents more than 93 percent of the cases.

Machine Learning for Predicting Patient Characteristics and Return Patterns

Armed with comprehensive data, we first developed machine-learning techniques to uncover patient characteristics, including resource needs, treatment outcome, LOS, and readmission patterns, and to establish predictive rules. A significant contribution of our work is that it is the first study in which demographics, socioeconomic status, clinical information, hospital operations, and disease behavioral patterns are employed simultaneously as attributes within a machine-learning framework.

The computational design of our machine-learning framework utilizes a wrapper approach; specifically, we apply pattern recognition based on our recent advances on text mining for unstructured clinical notes to the input attributes (Hagen et al. 2013). Next, we couple a combinatorial attribute-selection algorithm with a discriminate analysis via a mixed-integer program (DAMIP) learning and classification module. The attribute selection, classification, and cross-validation procedures are wrapped so that the attribute-selection algorithm searches through the space of attribute subsets using the cross-validation accuracy from the classification module as a measure of goodness. The small subset of attributes returned from the machine-learning analysis can be viewed as critical patient and clinical and (or) hospital variables that drive service characteristics. This provides feedback to clinical decision makers for prioritization and intervention of patients and tasks.

In the ED study, entities correspond to patients. The input attributes for each patient include comprehensive demographics, socioeconomic status, clinical information, hospital resources and utilization, and disease behavioral patterns. The machine learning uncovers patient disease patterns, associated resource needs, and factors influencing treatment characteristics and outcome. For readmission, there are two statuses for patients: they come back to the hospital for visits (return group), or they do not come back (nonreturn group). The classification aims to uncover from the set of all attributes a set of discriminatory attributes that can classify each patient into the return or nonreturn group. We seek to identify the rule that offers the best predictive capability.

In this supervised classification approach, the status of each patient in the training set is known. The training set consists of a group of patients extracted from the hospital database whose status (e.g., returned within 72 hours after the first visit or within 30 days after the first visit) is known. The training data are input into the machine-learning framework. Through the attribute-selection algorithm, a subset of attributes is selected to form a classification rule. This rule is then used to perform 10-fold cross-validation on the training set to obtain an unbiased estimate.

In 10-fold cross-validation, the training set is randomly partitioned into 10 roughly equal subsets. Of the 10 subsets, one subset is retained as the validation data for testing the model, and the remaining nine subsets are used as training data. The cross-validation process is then repeated 10 times (the folds), with each of the 10 subsets used exactly once as the validation data. The 10 results from the folds can then be averaged to produce an unbiased estimation. The advantage of this method over repeated random subsampling is that all observations are used for both training

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and validation, and each observation is used exactly once for validation.

To gauge the predictive power of the rule, we perform blind prediction on an independent set of patients; these patients have never been used in attribute selection. We run each patient through the rule, which returns a status. We then give the hospital personnel the predicted status of each patient, which they check against the patient's actual status. Hence, we always compare our prediction with the actual outcome in measuring predictive accuracy.

Once our machine-learning system sends a trigger that a particular patient is highly likely to return, an expert human (usually a nurse) places this patient on a to-observe list. That our predictions are not 100 percent accurate is understandable; however, the first pass is critical because it narrows down the return to a very small subset of patients, allowing the human expert to focus on them to determine which patients in this selected set should be observed in the clinical decision unit. Learning is continuous because human experts may identify attributes that they will use in their second pass of selection. These attributes will then be incorporated into our system for learning and refinement. Lee et al. (2003), Lee (2007), Lee and Wu (2007), Brooks and Lee (2010), and (2014) detail the DAMIP modeling and its theoretical and computational contributions. We include a mathematical formulation in the appendix. Briefly, DAMIP employs a 0-1 variable to denote if an entity is classified correctly. The model includes features that do not simultaneously exist in other classification models: (1) a mathematical expression that transforms the high-dimension attribute space into the group space to describe the group to which an entity will be classified; (2) a reserved-judgment region that handles entities whose group status is difficult to determine correctly to avoid overtraining and facilitate multistage classification; and (3) constraints on the percentage of misclassifications in each group. The model seeks to maximize the number of correct classifications.

DAMIP's special characteristics include the following: (1) the resulting classification rule is strongly universally consistent, given that the Bayes optimal rule for classification is known (Brooks and Lee 2010); (2) the misclassification rates using the DAMIP method are consistently lower than with other classification approaches when tested on both simulated and real-world data; (3) the DAMIP classification rules appear to be insensitive to the specification of prior probabilities, yet capable of reducing misclassification rates when the number of training entities from each group is different; and (4) the DAMIP model generates stable and robust classification rules regardless of the proportions of training entities from each group (Brooks and Lee 2010, 2014; Lee 2007; Lee and Wu 2007; Lee et al. 2003; Hagen et al. 2013; Koczor et al. 2013).

Note that, mathematically, DAMIP is proven to be NP-complete (Brooks and Lee 2010, 2014). We solved the instances for this ED study using advances in hypergraphic theory (Lee and Maheshwary 2013, Lee et al. 2014). Based on previous studies, the DAMIP approach generally works better than other machine-learning methods for unbalanced and heterogeneous data, as we encountered in this project (Lee et al. 2012a).

The Computerized ED System Workflow Model

To establish a framework for modeling and optimizing the ED workflow, including ED processes and dependencies on other hospital divisions when discharging patients from the ED, we use the RealOpt© simulation-optimization decision support environment (Lee et al. 2006a, b, 2009, 2011, 2012b, 2013a; RealOpt 2012). RealOpt was developed at Georgia Tech for the purpose of optimizing operations, throughput, and resource allocation for public health resources, in particular for emergency response and public health medical preparedness. It includes easy-to-use drawing tools to permit users to enter the workflow via mouse clicks and keystrokes. It also allows incorporation of the stochastic nature of human behavior (both the servers and patients) in workflows and processes, and provides a method to model fatigue and stress factors. In the background, it translates the workflow into a computerized simulation model in which resources can be optimized to achieve the best throughput and system performance. Figure 3(a) shows the (simplified) clinic workflow and service zones for Grady's ED, as entered into RealOpt via its graph-drawing panel.

Figure 3(b) shows the average total time to admit a patient from the ED to different units of the hospital.

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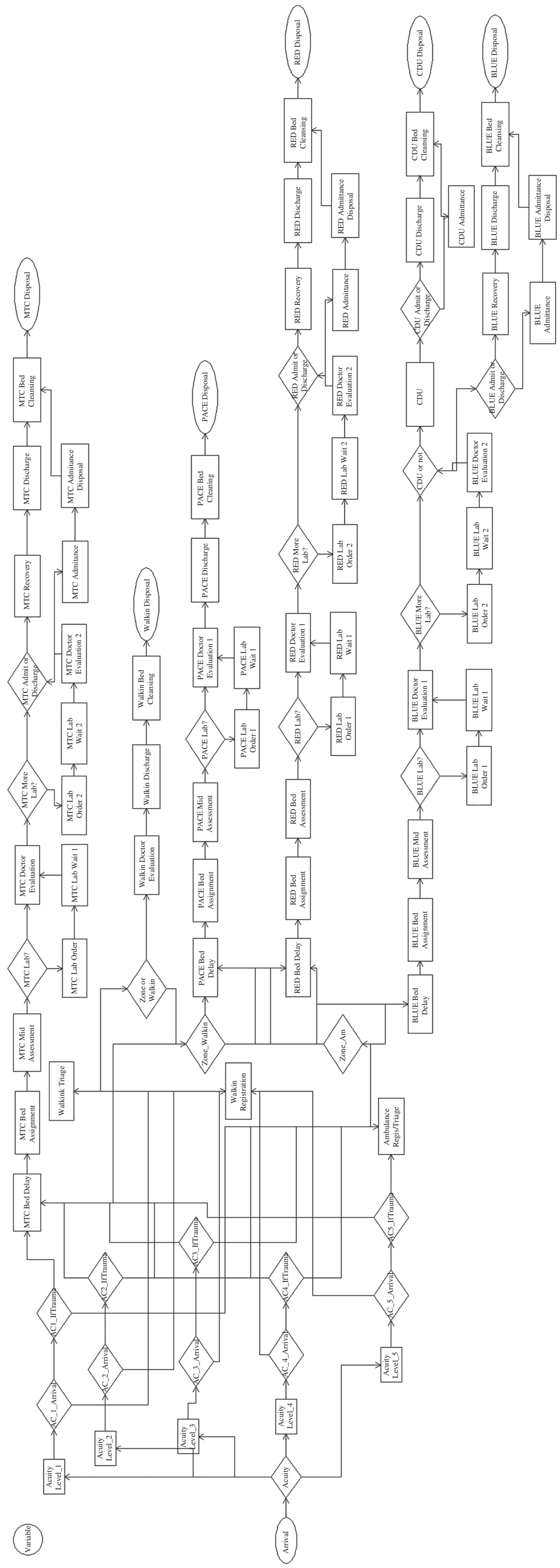
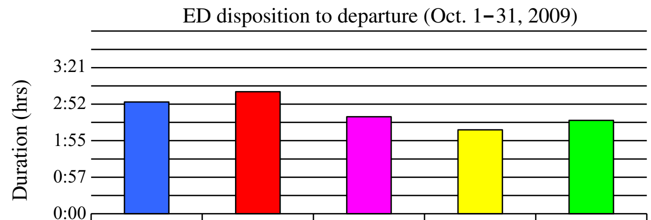


Figure 3(a): This RealOpt flowchart represents a simplified ED workflow at Grady.



	Tele	ICU	Floor	Isolation	Stepdown
Avg.	2:56	3:12	2:32	2:12	2:27
Min	0:55	1:20	0:35	1:10	1:00
Max	14:45	7:30	23:15	5:42	10:00
Count	61	34	132	17	36

Admit type

Figure 3(b): (Color online) The figure shows discharge destinations for October 2009 ED patients and the time taken from ED disposition to actual departure for each destination. Destinations are the telemedicine sign-up, intensive care unit, floor (normally staffed inpatient unit), isolation unit, and the stepdown unit (provides intermediate care between the ICU and floor).

Note that until the patient is admitted elsewhere, ED resources (in particular, the patient's bed) are not free to assign to a new patient. This information forms part of our RealOpt model for systems optimization.

Within RealOpt, optimization can be performed to ensure the best operations and system performance (e.g., throughput, wait time, queue length, utilization). The resource allocation is modeled via a nonlinear mixed-integer program (NMIP). Resource examples include labor, equipment, and beds. Constraints in the model include (1) maximum limits on wait time and queue length, which are dictated by the capacity of the waiting room in most EDs, and the desire to quickly service patients; (2) range of utilization desired at each station; (3) for each resource group, assignability and availability of resource types at each station (i.e., the skill set and the numbers of skilled personnel available); and (4) maximum limit on the cycle time of the individual (i.e., ED LOS). The system parameters in the simulation (i.e., queues, wait time, utilization, cycle time, and throughput) are performance variables in the optimization. Because some functions in the objective and constraints are not necessarily expressible in closed form, the problem is intractable by commercial systems. RealOpt is designed to overcome such computational bottlenecks by interweaving rapid system simulation and optimization (Lee et al. 2013a, b). The appendix includes further details on the model.

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As we describe previously, machine learning is used to identify discriminatory attributes that can predict whether a patient will return to the ED. Within the simulation, an individual patient is simulated thoroughly, including medical conditions, arrival times, zones visited, and treatments received. Hence, in addition to modeling the hospital operations, it also characterizes each individual by disease type, risk factors, demographics, and payer types—knowledge that the machine-learning analysis uncovers. Upon completion of a patient's treatment and before discharge, the machine-learning classification rule is used within the simulation environment to predict whether that patient will return. If it predicts that the patient will return, it triggers an alarm; a nurse then determines if the patient should be sent to the clinical decision unit for observation.

The novelty herein is the incorporation of patient characteristics and care patterns that the machine-learning framework uncovers within the RealOpt simulation-optimization environment. Hence, agents (representing patients) within the simulation present disease symptoms that challenge the care providers. They mimic the behavior of returning patients for whom certain symptoms may not have been diagnosed properly during previous ED visits. Further, the model captures more than 200 processes, including ED connected environments (e.g., discharge destinations and factors external to ED), which contribute to delays in the ED workflow. The optimization component connects the multiple-resource allocation, as we describe earlier, with process and operations optimization over the entire ED process network. The multiple-objective function values are evaluated through the simulation process.

Model Validation

Using the data collected, we simulated the hospital environment and operations, and validated the simulation results against an independent set of three months of hospital data. The model returned ED LOS, throughput, wait time, queue length, and other system statistics that are useful for performance measurement and comparison. For brevity, Table 2 includes only LOS and throughput comparisons. The simulation results accurately reflect the existing ED system performance, with outcome metrics and performance statistics consistent with their actual hospital values.

The average characteristics of Grady's ED patients differ markedly from national averages, especially because so few have private insurance. In 2009 at Grady, only eight percent of the ED patients had private insurance; more than 50 percent self-paid for the service, and Medicaid and Medicare paid for 36 percent. In contrast, nationally, approximately 50 percent of ED patients have private insurance. Moreover, Grady is burdened by return visits from uninsured individuals who use the ED as their primary care facility. Table 3(a) shows Grady's ED

	Phase I: Train: Aug. 2008–Feb. 2009 Validate: March–May 2009				Phase II: Train: Oct.–Dec. 2010 Validate: Jan.–March 2011			
	Hospital statistics		Simulated values		Hospital statistics		Simulated values	
ED zone	LOS (hours)	Patient volume*	LOS (hours)	Patient volume	LOS (hours)	Patient volume	LOS (hours)	Patient volume
Overall	10.59	8,274	10.49	8,446	7.97	8,421	8.02	8,398
Blue zone	14.54	2,141	13.90	2,137	11.40	2,107	11.78	2,126
Red zone	12.54	2,097	11.96	2,140	8.98	2,083	8.37	2,133
Trauma center**	7.85	271	7.98	251	6.80	268	6.86	259
Detention	13.85	437	12.93	407	10.90	441	10.53	432
PACe	7.90	2,037	8.60	1,983	5.10	1,920	5.60	1,983
Walk-in	3.20	990	3.30	992	2.50	950	2.88	940

Table 2: This table shows actual and simulated 30-day average LOS and throughput at Grady Hospital.
Note. **Remainder patients: *301 of the patients in this column include those who left before being seen, transferred to another facility, or provided no information. **These are airlift level 1 trauma patients. Grady treats roughly 1,542 trauma patients per month; many enter through the ED and are treated in the blue zone.**

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Nov.–Dec. 2009	72-hour return			30-day return	
Acuity level	No. of visits	No. of revisits	Percentage of revisits	No. of revisits	Percentage revisits
Total	15,168	824	5.43	3, 279	21.62
1: Immediate	367	17	4.63	56	15.26
2: Emergent	2,793	157	5.62	651	23.31
3: Urgent	6,595	385	5.84	1, 531	23.21
4: Less urgent	3,310	147	4.44	651	19.67
5: Nonurgent	1,531	90	5.88	294	19.20
None—missing	572	28	4.90	96	16.78

Table 3(a): ED readmission statistics for the period from November to December 2009 are shown.

	72-hour return		30-day return	
Acuity level	10-fold cross-validation (%)	Blind-prediction accuracy (%)	10-fold cross-validation (%)	Blind-prediction accuracy (%)
1: Immediate	83.9	82.7	78.3	75.4
2: Emergent	70.0	70.0	79.7	79.0
3: Urgent	70.1	70.5	78.5	78.5
4: Less urgent	71.1	70.1	80.2	80.0
5: Nonurgent	70.5	70.5	77.0	78.5
None—missing	75.3	74.7	89.8	91.1
Overall	71.0	71.1	79.3	78.7
		Payment type		
Private insurance	86.5	85.9	84.7	84.8
Self-pay	67.1	67.3	76.9	76.6
Medicare	70.1	70.9	77.5	77.9
Medicaid	66.1	67.4	76.5	76.7

Table 3(b): The table illustrates 10-fold cross-validation results and blind-prediction accuracy for 72-hour and 30-day returns. The percentage represents the percentage of patients with correct predictions.

readmission statistics for November to December 2009, which were close to the national average.

Our goal in predicting readmissions is twofold: (1) capture the characteristics of the disease and treatment patterns of readmitted patients to incorporate their behavior within the simulation-optimization environment; and (2) provide real-time guidance to ED providers to identify individuals (for observation) before discharge to mitigate the number of avoidable readmissions. Reducing the number of readmissions improves quality of care and provides financial and resource savings.

We apply the machine-learning framework using a training set of 42,456 patients, and blind predict using an independent set of 18,464 patients to gauge the predictive accuracies. Table 3(b) summarizes the results. We select those results in which both the specificity and sensitivity are above 70 percent. Note that for self-pay and Medicaid patients, the accuracy is below 70 percent. We also observe that predicting insured individuals yields the highest accuracy, because insured individuals use the ED only when necessary. Obtaining high prediction accuracy for patients who are not privately insured (e.g., self-pay, Medicaid, Medicare) is difficult. We also note that for 72-hour returns, prediction accuracy is highest for acuity-level 1 patients, because their symptoms and conditions are generally more conspicuous; in addition, 72-hour returns and 30-day returns show variations.

Computational Results, Implementation, and ED Performance Comparison

Phase I: Results

We performed systems optimization of the overall ED processes. In addition to the ED processes, the system model included other units in which ED patients are being discharged, for example, the ICU, stepdown, floor, isolation unit, and telemedicine sign-up. In Table 4(a), we summarize the operational performance according to improvement options using LOS and throughput. When we optimized over the existing ED layout, the system returned a global solution, which comprises Options 1–4. When we relaxed the layout restriction and optimized, it returned Options 1, 2, and 5 as the solution. Although these global solutions include a collection of changes and recommendations that together result in the best overall operations improvement, we split the solution into individual options and individually simulated the effects of these changes to allow for prioritization and selection by hospital management for implementation.

Specifically, we separated the global solution into five options according to change potential, and analyzed the anticipated ED operations improvement. Next, we describe the five options and their predicted impact.

Option 1. Combining registration and triage decreases the LOS of blue- and red-zone patients by more than one hour, with more significant gains by the most

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	Actual hospital operations	Simulation systems performance						
	March–May 2009		Systems improvement					
	Actual hospital statistics	Simulation output (using Aug.–Dec. 2008 observed data for training)	System solution (Options 1–4)	Option 1: Combine registration and triage	Option 2: Reduce lab/X-ray turnaround (−15 min)	Option 3: Optimize staffing in blue and red zones	Option 4: Optimize staffing in triage, walk in, and PACe	Option 5: Combine blue and red zones with optimized staffing
Overall								
Patient volume	8,274	8,446	8,413	8,433	8,324	8,392	8,401	8,331
LOS (h)	10.59	10.49	7.33	10.02	9.22	9.84	9.49	7.68
Average total wait time (h)	4.51	4.34	1.39	3.95	2.50	3.87	3.64	1.76
Blue zone								
Patient volume	2,141	2,137	2,135	2,138	2,139	2,145	2,139	4,273
LOS (h)	14.54	13.9	11.08	12.89	11.83	13.38	14.00	8.70
Red zone								
Patient volume	2,097	2,140	2,129	2,142	2,137	2,145	2,140	See above
LOS (h)	12.54	11.96	8.64	11.34	10.34	10.62	12.01	See above
Trauma								
Patient volume	271	251	251	250	249	251	251	271
LOS (h)	7.85	7.98	6.94	7.51	7.49	7.74	7.98	7.70
Detention								
Patient volume	437	407	410	411	410	408	411	401
LOS (h)	13.85	12.93	10.17	13.95	11.36	12.46	13.95	9.16
PACe								
Patient volume	2,037	1,983	1,970	1,988	1,966	2,001	1,979	1,989
LOS (h)	7.90	8.60	3.64	8.60	7.95	7.74	4.03	6.63
Walk in								
Patient volume	990	992	989	997	996	990	998	971
LOS (h)	3.20	3.30	1.9	3.31	2.86	3.2	2.49	2.94

Table 4(a): The table shows ED LOS and throughput comparisons for various systems improvement strategies.

severe (i.e., blue zone) patients. Detention patients are registered separately; thus, they do not benefit from the change. We find no change in how trauma patients are admitted, and marginal improvement for less urgent patients.

Option 2. Reducing laboratory and X-ray turnaround time (by 15 minutes) drastically reduces blue-zone, red-zone, and detention patients' LOS by more than two hours. These savings are realized because 59 percent of these patients require one laboratory order and 40 percent require two orders. The gain is also realized for trauma patients, although to a lesser extent. PACe and walk-in patients seldom require laboratory or X-ray orders. The time reduction is achieved via bin-tracking on orders and improved scheduled pickup and delivery between the ED and the laboratory.

Option 3. Optimizing staffing in blue and red zones reduces the LOS of blue- and red-zone patients by more than one hour, with more significant reductions observed by red-zone patients, because nurses originally operated at about 80 percent capacity in the blue zone and at 91 percent in the red zone. Detention-patient LOS also decreases because of using blue-zone resources.

Option 4. Optimizing staffing in triage, walk-in, and PACe areas reduces LOS by about 30 minutes for blue- and red-zone patients; as expected, it has a major impact on PACe and walk-in patients, reducing LOS by 3.8 hours (−49 percent) and 42 minutes (−22 percent), respectively.

Option 5. Combining blue- and red-zone layouts with optimized staffing offers substantial operational efficiency. Before the ESI was introduced, patients were sent to each color zone for similar complaints and (or) severity, as set forth by hospital personnel, to streamline the treatment process, to be assigned to appropriate providers, or to anticipate complexity

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of treatment. This also made revisits easier because patients would recall their previously assigned color zone. With the establishment of the ESI and sophisticated triage, patients are assigned an acuity level to assist in the treatment process. The color zones no longer serve their original purpose, although the hospital retains them (and appropriately uses them to accommodate the ESI). At Grady, the blue and red zones are adjacent to each other and share the same labor resources. Providers spend a good part of each day walking back and forth between these two zones tending to patients. Our combined layout with optimized staffing provides operational efficiency, because it reduces LOS by more than five and three hours for the blue and red zones, respectively, and reduces more than 40 percent of blue-zone LOS and 30 percent of red-zone LOS. Detention patients use blue-zone resources and achieve a LOS reduction of about 26 percent. As expected, LOS for trauma patients improves only slightly.

In addition to the systems optimization, our time-motion studies and machine-learning analysis also led us to make the following recommendation to hospital management.

Option 6. Allocate a separate area for walk-in patients to be assigned a bed instead of at the ambulance triage area.

Option 7. Eliminate batching patients from the walk-in area to a zone or PACe. Instead of accumulating enough patients and taking a group of them to a zone or PACe, service each patient based on his (her) arrival time.

Option 8. Eliminate batch discharges. Discharge paperwork is performed for each patient whenever that patient is ready for discharge, rather than discharging them in groups.

Option 9. Create a clinical decision unit to observe patients before formal discharge to reduce avoidable readmissions as a result of insufficient care, discrepancies in diagnosis, or premature discharge. This option arises from the machine-learning analysis that predicts patients who would be readmitted; providers then observe them to mitigate the readmission probability. This area is created by system optimization, which repurposes three beds from the blue zone and four beds from the red zone. Since 2003, Grady had an observation unit with six beds to manage ED patients for whom extra time is required to determine discharge or hospital admission. The repurposed seven beds increase Grady's ED observation capacity.

Option 10. Redirect nonurgent or walk-in patients to an alternative care facility.

Phase I: Adoption and Implementation

Grady management adopted Options 1–4, 7, and 8 for implementation, but made a minor alteration to Option 1—it combined the registration and triage only at the ambulance arrival area. These changes, which required no extra resources, were implemented by July 2009.

At that time, Option 9 was under discussion for implementation because we recommended reallocating or reoptimizing existing resources (i.e., labor, space, equipment). Option 10 was under consideration to raise funds to help pay for establishing the alternative care facility.

Subsequently, based on follow-up time-motion studies and independent best-practice benchmarking tools that Grady employs (e.g., CMS core measures, National Association of Public Hospitals (NAPH) quality indicators, Press Ganey, and Leapfrog quality indicators), the changes implemented by July 2009 led to a LOS reduction of about three hours (from more than 10 hours to slightly more than seven hours), as Table 4(b) shows for the Phase I adoption and implementation. In January 2011, the hospital implemented the recommended clinical decision unit for observation, using the machine-learning prediction to trigger the targeted treated ED patients for observation. Figure 4 shows the actual reduction of 72-hour and 30-day return patients. For acuity levels 1 and 2, 72-hour returns decreased by more than 30 percent and 7 percent, respectively. For 30-day returns, the reductions for these two levels were 24 percent and 9 percent, respectively. Our Grady ED transformation was timely. As a result of requirements in the Affordable Care Act, the hospital does not receive payment for return visits; in addition, it must pay a penalty. Hence, reducing avoidable readmissions represents improved care quality and provides financial savings.

These improvements raised confidence in our recommendations, and prompted the hospital to use $1 million of a donation from Kaiser Permanente to act on Option 10 of our recommendations—to open an

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Phase I: Comparison of ED performance (actual hospital monthly statistics)

	Original		Implementation of recommendations					
			Options 1–4, 7, 8		Options 1–4, 7–9 (clinical decision unit for observation)		Options 1–4, 7–10 (redirect nonurgent visits to walk-in center)	
	March–May 2009		July 2009–Dec. 2010		Jan.–Aug. 2011		Sept.–Dec. 2011	
ED zone	LOS (l^*) (h)	Patient volume	Reduction in LOS ($l - l^*$) (h)	Patient volume	Reduction in LOS ($l - l^*$) (h)	Patient volume	Reduction in LOS ($l - l^*$) (h)	Patient volume
Overall	10.59	8,274	−3.00	8,395	−2.86	8,421	−2.29	8,364
Blue zone	14.54	2,141	−3.26	2,525	−3.14	2,317	−3.22	2,603[a]
Red zone	12.54	2,097	−3.78	2,109	−3.80	2,230	−3.60	2,254
Trauma center	7.85	271	−1.01	252	−1.19	283	−1.22	305[a]
Detention	13.85	437	−3.12	420	−2.95	446	−3.01	445
PACe	7.90	2,037	−3.02	2,104	−3.18	2,098	−3.60	2,083
Walk-in	3.20	990	−1.0	945	−0.85	970	−1.2	510[b]

Table 4(b): The table shows 30-day average LOS and throughput performance following the initial Phase I implementation.
[a]The new trauma center was opened in November 2011.
[b]A significant number of nonurgent ED patients have been redirected to the new walk-in center since August 19, 2011, thus resulting in a significant decrease in ED walk-in patients.

alternative care facility, a walk-in center for low-acuity patients. This facility opened in August 2011 (Williams 2011). With confidence in improved ED efficiency, in October 2011, Grady also unveiled the Marcus Trauma Center, which increases the number of trauma beds from four to 15 (PRNewswire 2014). Based on the improved ED efficiency, our study recommended only one additional attending physician.

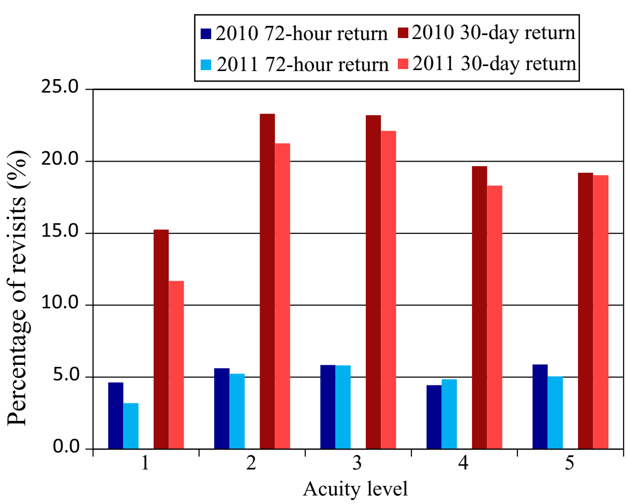

Figure 4: (Color online) The graph compares the percentage of ED revisits in 2010 and 2011. Note the significant reduction in 72-hour and 30-day returns following the installation of the clinical decision unit in 2011.

Phase II Results

In conjunction with the walk-in-center option and the increase of beds in the trauma center from four to 15, the hospital gained an attending physician; however, the ED demand also increased. The hospital observed a slight increase in LOS from 7.9 hours to more than 8 hours. Understanding that system improvement is an on-going effort in aligning demand with resources, the team embarked on Phase II of the system optimization effort using existing resources.

In the following summary, we omit the performance report for the PACe and walk-in, because the system output from the various strategies offers only marginal LOS differences compared to the larger improvements observed from Phase I.

Table 5(a) summarizes the anticipated results based on simulation and optimization. Specifically, globally optimizing the system resulted in an overall LOS reduction of 90 minutes. This entails global resource allocation and changes in ED layout. The improvement is considerable, with major LOS reductions in the blue and red zones (44 percent and 30 percent, respectively). Although the trauma center significantly

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	Actual hospital operations Aug.–Dec. 2011	Simulation systems performance: Global strategy: System optimization (resource + layout)	Simulation systems performance: Option 11: Optimize worker allocation	Simulation systems performance: Option 12: Combine blue and red zones
Overall LOS (hours)	8.30	6.79 (−1.51)	7.21 (−1.09)	6.94 (−1.36)
Blue zone (hours)	11.32	6.24 (−5.08)	6.66 (−4.66)	6.61 (−4.71)
Red zone (hours)	8.94	6.24 (−2.70)	6.19 (−2.75)	6.61 (−2.33)
Trauma center (hours)	6.63	6.46 (−0.17)	6.16 (−0.47)	6.47 (−0.16)

Table 5(a): Phase II comparisons of potential ED performance show efficiency improvements using different strategies.

Phase II: Comparison of ED performance (actual hospital monthly statistics)

	Original (from Phase I improvement)	Implementation of Phase II recommendations	
		Option 11 (optimizing overall ED staffing)	
	Sept.–Dec. 2011	2012	Jan.–Dec. 2013
ED Zone	LOS (I^{**})	Reduction in LOS ($I - I^{**}$)	Reduction in LOS ($I - I^{**}$)
Patient volume	8,364	8,920	9,060
Overall LOS	8.30 h	−1.00 h	−1.16 h
Blue zone	11.32 h	−3.95 h	−4.05 h (−36%)
Red zone	8.94 h	−2.70 h	−2.52 h (−30%)
Trauma center	6.63 h	−0.35 h	−0.30 h (−5%)

Table 5(b): The 30-day average LOS and throughput performance improved as a result of the Phase II implementation.

increased its bed capability, it added only one attending physician. As a result, trauma LOS improved by only about 10 minutes, because the new facility had a significant increase in trauma patients. Nevertheless, for trauma patients, particularly those who suffer from traumatic brain injury, 10 minutes can have a tremendous impact on outcome (e.g., survival, disablement, death), and is vital to the survival and quality of life of these patients.

Splitting the global strategies into Option 11 (optimal staffing) and Option 12 (optimal layout) resulted in similar minor LOS improvements in trauma patients. However, blue- and red-zone patients continued to enjoy significant LOS reductions.

Phase II: Adoption and Implementation

Table 5(b) contrasts the ED performance before and after the Phase II Option 11 implementation. Using existing resources and facility layout, Grady gained efficiency and timeliness of care by simply globally optimizing resources across the ED. The net LOS reduction of four hours for high-severity patients (i.e., blue zone) is substantial and could translate to better quality of care and outcomes. Even minor improvements in timeliness of care for trauma patients could make a difference between life and death, and have a significant impact on quality of life for these patients.

Combining blue and red zones is viable because all patients entering either zone require a consultation and generally require multiple resources or extensive diagnostic testing. However, such layout redesign may not be desirable, because commingling patients with different acuity levels may have detrimental effects on the treatment process; for example, care providers may not be as focused. The net gain of combining the zones, even with optimizing resource usage across all areas, is less substantial for trauma patients. The hospital executives carefully weighed this option, and are now confident that combining the zones will have an overall positive impact. At the time of this writing, the hospital has received $77 million of sponsored funding and has embarked on the ED facility layout redesign.

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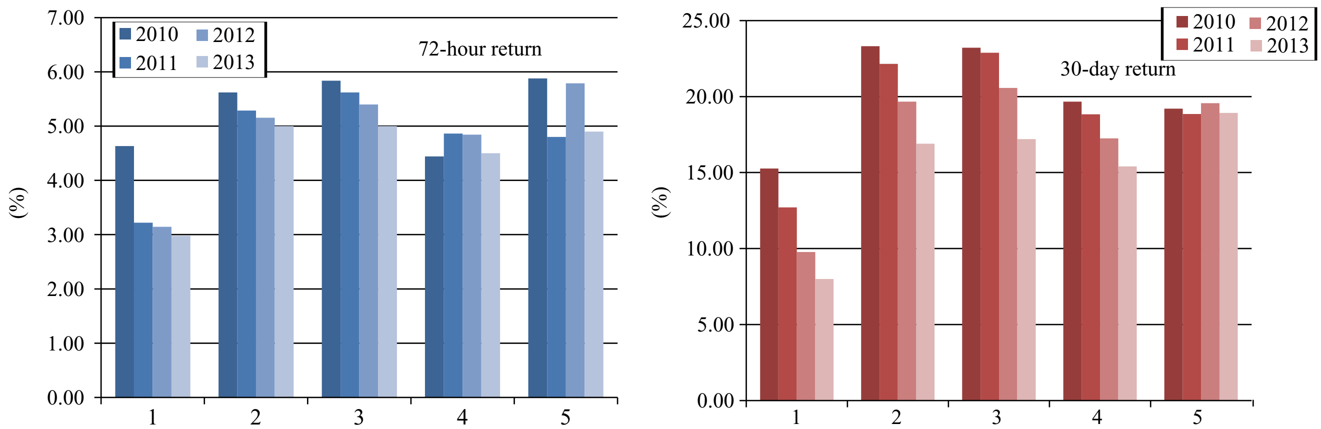

Figure 5: (Color online) The graphs compare the percentage of ED revisits in 2010 (no intervention), 2011 (Phase I), and 2012–2013 (Phase II). Note the significant drop in 72-hour and 30-day returns following the Phase I implementation. The machine-learning tool learns from revisit patterns and improves progressively as it adapts through the years. The level 4 and 5 patients who use the ED as their primary care service (i.e., super utilizers) remain a challenge, especially for 72-hour returns.

To monitor the performance of the clinical decision unit, Figure 5 contrasts the 72-hour and 30-day return performance for 2010–2013. Between Phase I and II, the 30-day return reduction shows substantial gain, especially among severe-acuity patients. Nonurgent patients (level 5) return to EDs at high rates because it is often their only means of access to healthcare. Such nonurgent readmission is unavoidable because some patients come in with unrelated health complaints. In contrast, although level 1 patients demand the most urgent care, their diagnosis is typically very specific; upon discharge, they are well counseled with regard to follow-up care with their primary care providers, resulting in lower returns to the ED. Mid-level acuity patients have higher rates of return because of the less-specific nature of their complaints and (or) diagnosis.

Figure 6 shows LOS trends for the ED zones through the various stages of implementation. Specifically, adoption of the initial optimization of overall staffing and process consolidation significantly reduced LOS across all zones (from the first to the second bar). This implementation did not require additional resources or financial investment. When the clinical decision unit was established in 2011, Grady experienced a marginal increase in LOS across all zones, because some patients were selected for observation to reduce potential returns (third bar). This also very slightly affected the LOS of the blue and red zones, because space and labor resources were repurposed for the clinical decision unit. In September 2011, the alternative walk-in center was opened, drastically reducing LOS for ED walk-in patients (fourth bar). The difference in LOS across other zones was marginal; however, overall LOS increased slightly because the

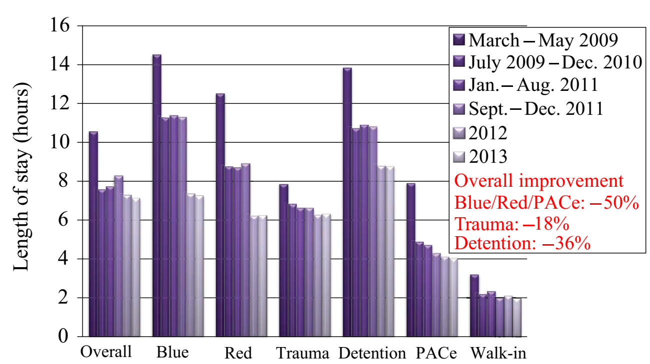

Figure 6: (Color online) The graph compares LOS from 2009 to the present. Grady has sustained a steady ED LOS since the 2009 system improvement implementation. The graph shows: March–May 2009 (original performance, first bar), July 2009–Dec. 2010 (after Phase I implementation, second bar), Jan.–Aug. 2011 (after implementation of the clinical decision unit for observation, third bar), Sept.–Dec. 2011 (after implementation of the walk-in center to redirect nonurgent patients, and expansion of the trauma center, fourth bar), and 2012–2013 (after Phase II implementation, fifth and sixth bars). The overall average LOS in 2013 was 7.14 hours.

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number of walk-in patients decreased significantly. Although the throughput in the ED and trauma center increased steadily over the years (by approximately 16.2 percent), the LOS from 2012 to the present stayed close to constant, indicating that the earlier improvement was being sustained. The clinical decision unit reduced potential avoidable returns, thus helping to save hospital resources, reduce penalties, and improve the quality of patient care. Since November 2013, the unit has expanded to 15 beds. The walk-in center has helped to relieve Grady's large healthcare burden of Medicaid and Medicare patients. By redirecting nonurgent ED patients, the hospital saved valuable resources and reduced the costs needed to unnecessarily treat these patients in the ED. This has also reduced the number of patients who leave without being seen by more than 32 percent.

Benefits and Impacts

This OR analytical work and the subsequent implementation and successes are extremely important to Grady. As a safety net healthcare provider, Grady must make transformative changes to improve efficiencies and reduce expenses so that it can continue to provide care to a significant segment of the population that is underserved medically. The goal of our work is to significantly improve the efficiency and timely delivery of quality care to Grady's ED patients. In the opinion of Grady executives and medical staff members, our OR analytical work made possible and substantially facilitated the benefits and impacts listed next.

Quantitative Benefits

Our work has improved the timeliness of emergency care. From the beginning of Phase I to the present, the overall average LOS decreased by 33 percent (10.59 hours to 7.14 hours), while average total waiting time decreased by 70 percent. This contrasts with an ED LOS of 8 to 11 hours in comparable safety net hospitals (see Table 6). The reductions are most significant for high-acuity patients: LOS decreased by more than 50 percent for both the blue and red zones (−7.27 hours and −6.28 hours, respectively); the LOS in the trauma zone decreased by 20 percent (−1.52 hours). Next, we list quantitative improvements.

Improved Efficiency of Emergency Care. Facilitated by the creation of the walk-in center, the improvements allowed Grady to increase its ED annual throughput (i.e., number of patients treated) by more than 7.8 percent (+8,114), its trauma volume by 8.4 percent (+1,664), and its volume of severe trauma cases (i.e., patients facing life-and-death situations) by 14 percent (+417), and reduce the number of patients who leave without being seen by more than 30 percent (−5,553). Moreover, it made these improvements without increasing its ED staff or facilities. The use of the clinical decision unit decreased avoidable 72-hour and 30-day readmissions among the acuity-levels 1–3 patients by 28 percent (−602). This produced direct financial and resource savings for the hospital and had a positive impact on patient-care quality measures. The alternative walk-in center serviced more than 32 percent of the nonurgent ED cases outside the ED treatment area, thus reducing the hospital's financial burden (by treating these patients in a lower-cost area) and ensuring proper ED resource usage.

Annual Financial Savings and Revenues. From 2008 to 2012, the reduction in revisits resulted in $7.5 million of savings in penalties. The walk-in center for

Hospital	LOS for ED patients discharged to hospital (hrs)	LOS for ED patients discharged home (hrs)	Average ED LOS
LAC/USC (Los Angeles)	17.8	6.7	8–11 hrs
Cook County (Chicago)	15.0	6.0	
Parkland (Dallas)	11.1	5.3	
Grady (2014)	9.3	6.7	7.1 hrs
Grady (2008) before improvement	13.5	10.0	10.6 hrs

Table 6: In this table, we compare the LOS in major safety net hospitals (http://www.Hospitalcompare.hhs.gov).

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nonurgent conditions reduced ED costs by $21.6 million and resulted in $12.5 million in additional revenue. ED and trauma efficiency increased the revenue by $96.6 million. Expansion of trauma care resulted in $51.8 million in revenue. For a critical safety net hospital with $1.5 billion of annual economic impact, only eight percent of which is paid by private insurance, the $190 million financial gains have a tremendous impact on maintaining Grady's financial health.

The ED, often called the front door to a hospital, serves as a source of hospital inpatient admissions, which on average generate more revenue than ED-only admissions. For Grady Hospital, the ED provides about 75 percent of inpatient admissions. Thus, the ED's increased throughput and other improvements played a major role in the significant revenue increases shown in Grady's annual financial reports.

Encouragement of External Sponsorship. In part, as a result of the rigorous OR-driven recommendations, Grady has been able to document success in timeliness of care and operational efficiencies, thus facilitating increased philanthropic donations. The Kaiser Foundation contributed $1 million (Williams 2011) to establish an alternative care site (walk-in center) for low-acuity patients. A $20 million gift from the Marcus Foundation (PRNewswire 2014) enabled Grady to create a world-class stroke and neuroscience center and a state-of-the-art trauma center. The OR advances and subsequent ED transformation give investors confidence in sponsoring projects that will benefit the hospital and its patients.

Qualitative Benefits

Our work has saved lives and reduced morbidity and disabilities. Efficient ED operations allow the ED to more quickly treat patients with time-sensitive conditions. The shortened LOS demonstrates that patients move from the ED and receive appropriate care in the appropriate setting in a timelier manner. For high-acuity patients, quicker response during the golden hour of treatment (i.e., a period of about one hour following traumatic injury) during which prompt medical treatment will likely prevent death can mean the difference between life and death, disability, or returning to a normal life. Faster door-to-computerized-tomography (CT) scan and door-to-tissue-plasminogen-activator (a clot-dissolving drug) administration for stroke patients, and faster door-to-antibiotics for pneumonia patients have decreased long-term disability and death. More acute trauma patients can be treated, saving more lives. Improved timeliness and service quality directly translate to improved quality of life for patients and decreased morbidity and mortality, and make a difference in whether a patient is treated and released, or is admitted to the hospital (see Table 7).

Health Cost Reductions. ED timeliness and efficiency of care have a broad impact on patient quality of life and healthcare spending. Timeliness and improved quality of care improve outcomes, and consequently lead to indirect savings of hundreds of millions of dollars in ongoing care and management of patients. In addition, reducing disability allows patients to lead normal lives. The estimate of the value of one life in the United States is $50,000–$100,000 per year of life saved (Owens 1998). We emphasize that although quality and systems efficiency have been our focus, the monetary savings (for both the providers and the patients) are real and critical to our national healthcare system. This is especially true for safety net hospitals such as Grady, which feel the burden more acutely than other hospitals, given that many of its service costs are not reimbursed.

ED service	2013 volume	Increase in volume	Reduced death and disability
Airlift trauma patients	3,395 patients	417 patients (+14%)	All need immediate care for life-and-death situations
Trauma patients	15,992	1,665 (+8.4%)	Death ~56 Disability ~160
Comprehensive care	39,059	2,001 (+5.52%)	Disability ~390
Extended care	29,645	902 (+2.9%)	Disability ~296

Table 7: These estimates of potential death and disability reductions resulted from increasing patient volumes at Grady in 2013. Volume increases shown compare 2013 and 2012.

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Continuous Improvement and Adaptive Advances. The hospital has been able to achieve its targeted goal of ED LOS of seven hours and sustain overall improvement for over five years. With ED demand continuing to grow, maintaining a culture of continuous improvement is key to sustaining good performance.

Improved Quality of Care in Other Facilities. The model can be generalized and has been tested and successfully implemented in 10 other EDs. The benefits across these EDs are consistent with the substantial benefits Grady achieved. The ED volumes at these 10 sites range from 30,000 to 80,000 patients per year. Upon implementation, they have experienced a total throughput increase from 15 to 35 percent, a reduction of revisits of severe acute patients from 19 to 41 percent, a LOS reduction from 15 to 38 percent, and a reduction in the number of patients who leave without being treated from 35 to 50 percent.

Grady has applied the technology in other units, including medication error analysis for the pharmacy and hospital-acquired conditions (HACs) in the ED, operating room, and intensive care units. HAC is one of the 10 major causes of death in the United States. Our surgical site infection (SSI) study at Grady involved reducing mediastinitis after cardiac surgery. Nationwide, the 700,000 open-heart surgeries performed each year result in infection rates of 0.5–5 percent. Of those infected, the mortality rate is 40 percent. On average, an additional 30 days of hospital LOS and (or) one extra surgical procedure are required. The SSI rate at Grady was 23 percent in 2010. The team implemented transformative changes, including strategic preoperative procedures for both inpatients and outpatients and optimal timing and dosing of preoperative antibiotics in July 2011. The infection rate decreased to 1.5 percent between July 2011 and January 2012, and has been zero percent since February 2012. The team is now conducting a study on joint surgeries, bloodstream infection, and catheter-induced urinary-tract infection.

Scientific Advances

The collaborative effort between hospital researchers and OR scientists resulted in scientific advances on two fronts, as follows.

Hospital Care Delivery Advances. The new system couples machine learning, and simulation and optimization decision support to improve the efficiency and timeliness of care in the ED, while reducing avoidable readmissions. The model allows a hospital to globally optimize its ED workflow, taking into account the uncertainty of human disease characteristics and care patterns, to drive the patient LOS and wait time to a minimum. It provides a comprehensive analysis of the entire patient flow from registration to discharge, and enables a decision maker to understand the complexities and interdependencies of individual steps in the process sequence; ultimately, it allows a hospital to perform systems optimization to achieve the most optimum performance.

The model focuses on system optimization that results in improvements in LOS and waiting time through resource allocation, system consolidation, and operations optimization without attempting to change the behavior of healthcare providers or patients. Rather, the system captures the human behavior and optimizes the workflow process to achieve optimal results. Although changing human behavior can result in significant gains, we understand that such changes may be more costly in terms of training and altering habits; this is particularly true for teaching hospitals at which rotations of residents and healthcare trainees are common. The potential to introduce new errors also exists. Thus, we accept the variability in human behavior and services and incorporate these elements into our model to reflect workflow and human characteristics.

OR Advances. The novelty of our OR-driven analytical work includes performing systems optimization within the ED simulation environment; incorporating treatment patterns and patient characteristics dynamically and stochastically within the ED operations and quality-improvement framework; modeling ED readmission using—simultaneously—demographics, socioeconomic status, clinical information, hospital operations, and disease behavioral patterns; modeling ED interdependencies involving other hospital units; and integrating a machine-learning framework within the simulation-optimization environment.

We acknowledge the computational challenges of such large-scale complex models in data collection for

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model validation, parameter estimation, and global system optimization. The machine-learning framework and the DAMIP model have been proven to be NP-hard (Brooks and Lee 2014); hence, they require both theoretical and computational breakthroughs (Brooks and Lee 2010, 2014; Lee 2007; Lee and Maheshwary 2013; Lee and Wu 2007; Lee et al. 2003, 2014). However, once the predictive rule has been established, it can analyze and predict patient return patterns in nanoseconds, opening up real-time target patient intervention. We derived polyhedral theory and applied it to the solution strategies for DAMIP (Brooks and Lee 2010, 2014; Lee and Maheshwary 2013; Lee et al. 2014).

Because of the complexity of simultaneously simulating dynamic system behavior and optimizing operational performance, solving within our simulation-optimization framework remains a challenge. We caution that our solutions, although obtained rapidly, are not proven to be optimal. Nevertheless, our investigations indicate that the solutions are close to optimal.

Future Plans

We acknowledge the proactive attitude of our healthcare collaborators who worked tirelessly to learn our system advances and present our recommendations to key stakeholders for change transformation to make this project a success. Challenges remain: the team will closely monitor the facility-layout redesign, and measure important outcome metrics to gauge its impact on overall performance and patient care. In addition, important regulatory compliances and critical and delicate issues related to mental health treatment must be addressed. We will also address the super utilizers, those underinsured patients who utilize the ED with up to 33 visits per month. Further, beyond the day-to-day operations, we will carry out strategic planning. The system developed allows healthcare managers to adapt the model as the ED environment and operations evolve. Moreover, work is underway to apply the system to improve efficiency and quality in other units. Such a dynamic and flexible computerized system is critical for sustained continuous operational improvement. It will help Grady adapt quickly to changes in the healthcare environment, and ensure its survival as an essential safety net hospital serving the Atlanta community and beyond.

Related photos, presentations, hospital-insider notes, and an Institute of Medicine/National Academy of Engineering letter concerning the significance of the work are available at http://www2.isye.gatech.edu/medicalor/EDadvances.

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Appendix

Optimization-Based Classifier: Discriminant Analysis via Mixed-Integer Program

In this section, we briefly describe DAMIP. Suppose we have n entities (e.g., patients) from K groups (e.g., returning or nonreturning) with m features. Let $\mathcal{G} = \{1, 2, \ldots, K\}$ be the group index set, $\mathcal{O} = \{1, 2, \ldots, n\}$ be the entity index set, and $\mathcal{F} = \{1, 2, \ldots, m\}$ be the feature index set. Also, let $\mathcal{O}_k$, $k \in \mathcal{G}$ and $\mathcal{O}_k \subseteq \mathcal{O}$, be the entity set that belongs to group k. Moreover, let $\mathcal{F}_j$, $j \in \mathcal{F}$, be the domain of feature j, which could be the space of real, integer, or binary values. The ith entity, $i \in \mathcal{O}$, is represented as $(y_i, \mathbf{x}_i) = (y_i, x_{i1}, \ldots, x_{im}) \in \mathcal{G} \times \mathcal{F}_1 \times \cdots \times \mathcal{F}_m$, where y_i is the group to which entity i belongs, and $(x_{i1}, \ldots, x_{im})$ is the feature vector of entity i. The classification model finds a function Ψ: $(\mathcal{F}_1 \times \cdots \times \mathcal{F}_m) \to \mathcal{G}$ to classify entities into groups based on a selected set of features.

Let π_k be the prior probability of a randomly chosen entity being in group k and $f_k(\mathbf{x})$ be the group conditional probability density function for the entity $\mathbf{x} \in \mathbb{R}^m$ of group k, $k \in \mathcal{G}$. Also let n_h denote the number of entities from group h, and $\alpha_{hk} \in (0, 1)$, $h, k \in \mathcal{G}$, $h \neq k$, be the upper bound for the misclassification percentage that group h entities are misclassified into group k. DAMIP seeks a partition $\{P_0, P_1, \ldots, P_K\}$ of $\mathbb{R}^K$, where P_k, $k \in \mathcal{G}$ is the region for group k, and P_0 is the reserved-judgment region with entities for which group assignment are reserved (for potential further exploration).

Let u_{ki} be the binary variable to denote if entity i is classified to group k. Mathematically, DAMIP can be formulated as **(DAMIP)** (Lee 2007, Lee et al. 2003).

$$\max \sum_{i \in \mathcal{O}} u_{y_i i} \tag{D1}$$

$$\text{s.t.} \quad L_{ki} = \pi_k f_k(\mathbf{x}_i) - \sum_{h \in \mathcal{G},\, h \neq k} f_h(\mathbf{x}_i) \lambda_{hk}, \quad \forall\, i \in \mathcal{O},\ k \in \mathcal{G}, \tag{D2}$$

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$$u_{ki} = \begin{cases} 1 & \text{if } k = \arg\max\{0, L_{hi}\colon h \in \mathcal{G}\}, \\ 0 & \text{otherwise}, \end{cases}$$

$$\forall\, i \in \mathcal{O},\; k \in \{0\} \cup \mathcal{G}, \qquad \text{(D3)}$$

$$\sum_{k \in \{0\} \cup \mathcal{G}} u_{ki} = 1, \quad \forall\, i \in \mathcal{O}, \qquad \text{(D4)}$$

$$\sum_{i:\, i \in \mathcal{O}_h} u_{ki} \le \lfloor \alpha_{hk} n_h \rfloor, \quad \forall\, h, k \in \mathcal{G},\; h \ne k, \qquad \text{(D5)}$$

$$u_{ki} \in \{0, 1\}, \quad \forall\, i \in \mathcal{O},\; k \in \{0\} \cup \mathcal{G},$$

$$L_{ki} \text{ unrestricted in sign}, \quad \forall\, i \in \mathcal{O},\; k \in \mathcal{G},$$

$$\lambda_{hk} \ge 0, \quad \forall\, h, k \in \mathcal{G},\; h \ne k.$$

The objective function (D1) maximizes the number of entities classified into the correct group. Constraints (D2) and (D3) govern the placement of an entity into each of the groups in $\mathcal{G}$ or the reserved-judgment region. Thus, the variables L_{ki} and λ_{hk} provide the shape of the partition of the groups in the $\mathcal{G}$ space. Constraint (D4) ensures that an entity is assigned to exactly one group. Constraint (D5) allows the users to preset the desirable misclassification levels, which can be specified as overall errors for each group, pairwise errors, or overall errors for all groups together. With the reserved judgment in place, the mathematical system ensures that a solution that satisfies the preset errors always exists.

Mathematically, we have proven that DAMIP is *NP-hard* and that the resulting classification rule is strongly universally consistent, given that the Bayes optimal rule for classification is known (Brooks and Lee 2010, 2014). Computationally, DAMIP is the first multiple-group classification model that includes a reserved judgment and the ability to constrain the misclassification rates simultaneously within the model. Furthermore, we have demonstrated in real-world applications that DAMIP works well by using a uniform prior probability and a normal group conditional probability density function. They serve to transform the attributes from their original space to the group space (Brooks and Lee 2010, 2014; Koczor et al. 2013; Lee 2007; Lee and Wu 2007; Lee et al. 2003, 2012a; Nakaya et al. 2011; Sturm et al. 2010). In Brooks and Lee (2010, 2014), we have shown that DAMIP is difficult to solve, and we applied the hypergraphic structures that Lee and Maheshwary (2013) and Lee et al. (2014) derived to efficiently solve these instances. Empirically, DAMIP can handle imbalanced data well; thus, it is suitable for the ED readmission analysis, when compared against other classification approaches (Lee et al. 2012a).

The predictive model maximizes the number of correctly classified cases; therefore, it is robust and not skewed by errors committed by observation values. The associated optimal decision variable values (L_{ki} and λ_{hk}) form the classification rule, which consists of the discriminatory attributes; examples include patient chief complaint, diagnosis, whether IV antibiotics were ordered, trainee and (or) resident involved, primary nurse, time when the patient received an ED bed to time until first medical doctor arrived. Using this rule, blind prediction of whether a new patient will return to the ED can be performed in real time.

One can use alternative objectives, for example, by placing different weights on each group. In Lee (2007), we discuss various alternative objectives that take into account differences in the relative cost of different types of classification errors. We tested these alternatives on hospital readmission studies (Lee et al. 2012a). For the paper herein, we report the best combination when applied to the Grady data.

Nonlinear Mixed-Integer Program for Multiple-Resource Allocation

The nonlinear mixed-integer program (MIP) used in allocating resources was built on top of the nonlinear MIP formulated in Lee et al. (2009) and solved using the simulation-optimization framework described in Lee et al. (2013a). In all three papers (including this work), an initial solution is obtained via a fluid model as a warm start to a resource optimization model; the results of the optimization are entered into a simulation model that estimates the system's average wait time, queue length, and utilization. If the solution satisfies all the input ranges, this solution is returned. Otherwise, the system looks for violated constraints (from among wait time, queue length, and cycle time), and determines violated service blocks. Service blocks are all the services and (or) processes that a patient might undergo in an ED visit, including triage, registration, PACe examination, walk-in, and laboratory tests. Once these blocks are identified, optimization will be performed on them. This time, however, the objective is to minimize a total violation penalty. The process continues until convergence.

There are two key distinctions between this work and the earlier work by Lee (e.g., Lee et al. 2012b, 2013a). First, machine learning that predicts patient pattern and treatment characteristics is integrated into the simulation-optimization decision framework. Second, this work models multiple resource groups at each station. The optimization within each simulation step maximizes throughput without exceeding the existing resources, and includes weights on how to use staff skills. For example, if a nurse and a physician can both perform a specific task, it may be more expensive to use a physician than a nurse (or vice versa). The user ranks them in the input, and we use these ranks as weights in the optimization process.

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