NOVEL METHODS TO FORECAST EMERGENCY DEPARTMENT CROWDING

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LIST OF ABBREVIATIONS

Abbreviation	Definition
AMOC	activity monitoring operating characteristic
AUC	area under the receiver operating characteristic curve
CI	confidence intervals
CPOE	computerized physician order entry
CT	computed tomography
DEEDS	Data Elements for Emergency Department Systems
ED	emergency department
EDCS	Emergency Department Crowding Scale
EDWIN	Emergency Department Work Index
EMR	electronic medical record
EMTALA	Emergency Medical Treatment and Active Labor Act
ESI	Emergency Severity Index
MeSH	Medical Subject Headings
NEDOCS	National Emergency Department Overcrowding Scale
READI	Real-time Emergency Analysis of Demand Indicators
ROC	receiver operating characteristic

CHAPTER I

INTRODUCTION

Problem Statement

The emergency department (ED) provides an essential medical service to society. A majority of people only seek treatment in the ED on rare occasions. Other people, including the uninsured and the indigent, frequently seek primary care in the ED. Both groups depend on the ED to be available when necessary; therefore the ED is aptly called the "safety net" of the health care system [1-2].

Unfortunately, the role of the ED as a safety net is now being threatened by a crisis of overcrowding. As shown in figure 1, the annual number of ED visits in the United States rose from 86.7 million in 1990, to 114.8 million in 2005 [3]. During the same period, the number of EDs decreased from 5,172 to 4,611. By consequence, 47% of American hospitals reported that they were operating at or over their ED capacity in 2007 [3]. This percentage is exacerbated in certain settings, particularly for urban (65%) and teaching (73%) medical centers. Recognizing this, the Institute of Medicine reported that the safety net of the health care system is "at the breaking point" due to the crowding issue [4].

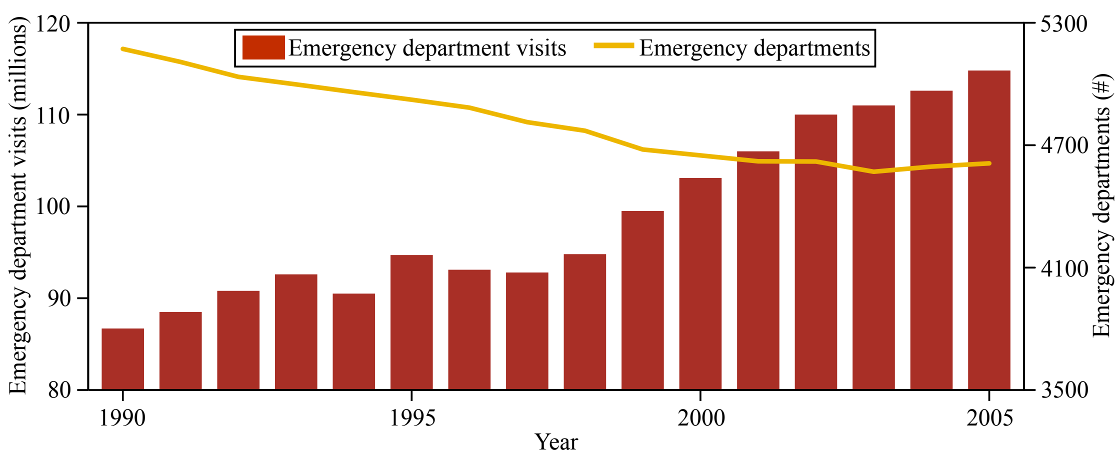

Figure 1. Trends in supply and demand for ED services in the United States, 1990 – 2005. Data were obtained from the 2007 American Hospital Association TrendWatch Chartbook [3].

Historical Context

A number of political and cultural factors may have laid the foundation for a crisis of overcrowding. The Emergency Medical Treatment and Active Labor Act (EMTALA), which was passed by the United States Congress in 1986 as part of the Consolidated Omnibus Budget Reconciliation Act, mandated that all patients who seek care in an ED must receive a medical screening examination [5]. The law was passed to prohibit the practice of patient dumping, whereby hospitals refuse to treat patients who might be unable to pay for care or incur high treatment costs. Thus, all patients are legally guaranteed to receive the same basic level of service in an ED, regardless of extenuating circumstances.

According to census data, the total number of Americans without health insurance rose to 44.8 million in 2005, representing 15.3% of the total population [6]. In addition, 40.2 million people were covered by Medicare, and 38.1 million people were covered by Medicaid. As shown in figure 2, these vulnerable populations visit the ED with substantially higher frequency than people with private insurance [7]. In a 1993 report, the United States General Accounting Office attributed crowding to the growth in visits among uninsured, Medicare, and Medicaid patients, many of whom seek primary care in the ED [8].

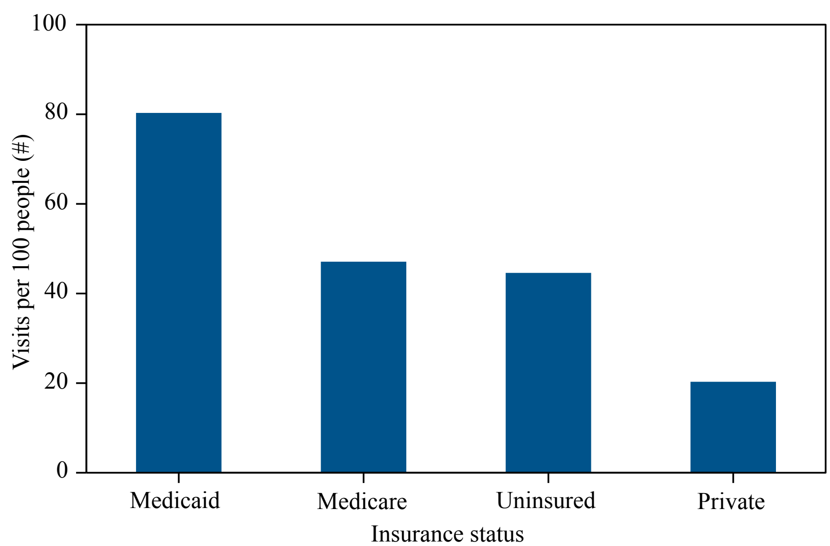

Figure 2. Annual frequency of ED visits among patients with differing insurance status. Data were obtained from the 2004 National Hospital Ambulatory Medical Care Survey [7].

More recent evidence suggests that uninsured and underinsured Americans may not be responsible for the majority of the surge in demand for ED services [9-10]. By contrast, frequent ED visitors are often insured and have regular access to primary care. A primary care setting may not have sufficient equipment to rule out certain potentially life-threatening diagnoses. Thus to be conservative, patients with shortness of breath, abdominal pain, or headaches are commonly referred to ED care, even though such complaints usually have benign underlying causes. Furthermore, the number of people living with chronic diseases in the United States is estimated to exceed 100 million [11]. The technologically advanced diagnostic tests and therapeutic strategies required to manage these patients may not be readily available in primary care settings, possibly prompting these patients to seek care in a hospital-based ED setting.

American hospitals are having difficulty coping with the volume of inpatient admissions. This causes some patients to board, or remain in the ED for extended periods of time while awaiting hospital beds. Between 1983 and 2005, the number of hospital beds in the United States decreased by 21.2% [3]. Moreover, a growing shortage of nurses, with a deficit of 219,000 full-time employees in 2005, prevents both hospital and ED beds from being staffed as necessary [3]. In 2003, a second report from the United States General Accounting Office concluded that boarding of patients in the ED had become a substantial contributor to the crowding problem [12]. The report noted two factors that motivate hospitals to practice inpatient boarding: First, economic pressure associated with managed care may have caused hospitals to reduce their capacity. Second, ED patients may receive lower priority when competing for hospital beds with other, potentially more profitable, patients, such as those scheduled for elective surgeries.

Although the preceding discussion focused on ED crowding in the United States, the problem appears to be widespread among developed nations, indiscriminately affecting private and socialized health care systems alike. Reports have identified and characterized ED crowding in numerous other countries including Canada [13], Great Britain [14], Spain [15], Australia [16], Taiwan [17], and Pakistan [18]. One editorial called ED crowding "an international symptom of health care system failure" [19].

Forecasting Crowding

The American College of Emergency Physicians noted that "the causes of crowding are multifactorial and span the entire health care delivery system" [20]. Therefore, it is possible that nothing short of a major societal change will permanently solve the ED crowding problem. However, providers and administrators remain liable to maintain health care quality and access to the greatest extent possible, despite the crisis. The following research will emphasize methods of helping stakeholders to cope with, rather than to eliminate, the problem.

The capacity of the health care system is generally fixed in the short term, although the inputs are variable and influenced by a myriad of factors. One strategy of alleviating ED crowding would involve permanently allocating extra resources to handle periods of high demand. However, this strategy would require significant capital investment, and the additional resources would become wastefully idle during quiet periods. The costs required to solve ED crowding in this manner may be unmanageable. To cope with crowding in the 21st century, EDs must become more agile, and they must gain the ability to rapidly mobilize resources as needed.

The concept of dynamic resource mobilization begs an important question, namely, when should an intervention be triggered? The answer to this question may fall within the realm of queuing theory [21]. The objective of this research may be consistent with one recommendation by the Institute of Medicine, who noted that "a growing body of experience suggests that using queuing theory to smooth the peaks and valleys of patient admissions can eliminate bottlenecks, reduce crowding, improve patient care, and reduce costs" [4].

This work occurs in the context of previous research that has proposed ways of measuring and forecasting ED crowding. Much of this work was influenced by a conceptual model that described ED crowding in terms of input-throughput-output components [22]. Input factors of crowding include the various populations and qualities that comprise the demand for ED care. Throughput factors of crowding include ED workflow and organizational issues that may lead to bottlenecks in patient flow. Output factors of crowding include discharge-related matters, particularly inpatient boarding, that originate downstream from the ED. Continuing this work, 74 experts on ED crowding were assembled to reach a consensus on 38 specific measures that could be used to quantify the input, throughput, and output aspects of crowding [23].

Several instruments have been described that express multiple facets of ED crowding in a single numerical measure. The Emergency Department Work Index (EDWIN) is a formula-based measure that takes into account the total patient burden, degree of sickness, attending physicians, and available beds [24]. The Real-time Emergency Analysis of Demand Indicators (READI) scores are formula-based measures that take into account the total patient burden, anticipated arrivals and departures, degree of sickness, rate of arrivals, and hourly physician productivity [25]. The National Emergency Department Overcrowding Scale (NEDOCS) is a regression-based measure that takes into account the burden of total and admitted patients, the boarding time, the waiting time, and the number of patients requiring mechanical ventilation [26]. The Emergency Department Crowding Scale (EDCS) is a regression-based measure that takes into account that burden of total, boarding, and critical patients [27]. The Work Score is a regression-based measure that takes into account the waiting room status, degree of sickness, and boarding patient burden [28]. All of the above measures describe the present crowding state of an ED, but they have not been evaluated for predicting the future crowding state.

Because dynamic resource mobilization may take a few hours to initiate, a forecasting system may provide more utility than a monitoring system. Thus, some studies have described time series models that can be used to forecast specific aspects of ED crowding. One group compared various time series analyses and found that simple models could be used to forecast patient arrivals and length of stay, but not sufficiently well to inform decisions about resource allocation [29]. Recently, another group developed a deterministic census model based on differential equations to capture the daily, cyclical pattern of patient flow, which may be useful for answering questions about operations research [30].

These techniques to measure and forecast ED crowding all make valuable contributions to the field, although the question of how to trigger interventions requiring dynamic resource mobilization has not yet been fully answered. All research in ED crowding is challenged by the fact that no standard, generally accepted definition exists for the term "crowding" [31]. Research in this field would not likely benefit from a situation like the Tower of Babel, where everyone speaks a different language. This project has no agenda to promote a single crowding definition, however – the definition will be left to professional and institutional preference. Instead, a novel application of discrete event simulation may allow providers, administrators, and researchers to forecast ED crowding in real time, regardless of how crowding is defined.

The fields of queuing theory and discrete event simulation share a close relationship: Many models based on queuing theory are too complex to evaluate by exact mathematics, so they are frequently evaluated stochastically through discrete event simulation [32]. The feasibility of representing ED patient flow using a discrete event simulation model was first reported in 1989, and the simulation accurately predicted the effects of hypothetical changes to the ED organization [33]. More recently, discrete event simulations have been developed and applied to project the effects of changing triage protocols and staffing schedules [34-36]. This dissertation will attempt to adapt the methods from these prior studies in a novel manner to forecast ED crowding.

Specific Aims

The broad purpose of this research is to leverage knowledge from queuing theory and discrete event simulation to enable dynamic resource mobilization as a means of alleviating ED crowding. To achieve this goal, four specific aims are addressed:

1: To conduct a systematic literature review on the causes, effects, and solutions of crowding.

2: To quantify the ability of previously described measures to monitor and forecast crowding.

3: To develop a simulation of patient flow for the purpose of anticipating future crowding.

4: To assess the potential impact of an intervention based on the forecast to alleviate crowding.

Chapter I describes the historical and societal context that motivates the proposed research. The four subsequent chapters present the body of research that is intended to address the Specific Aims. Chapter II details a systematic literature review on the causes, effects, and solutions of ED crowding to address Specific Aim 1. Chapter III describes a prospective, independent validation of four crowding measures to address Specific Aim 2. Chapter IV presents the development and preliminary validation of a discrete event simulation to address Specific Aim 3. Chapter V describes the real-time deployment and prospective validation of the simulation tool to address Specific Aim 4. Chapter VI concludes the dissertation with a summary of the key contributions, together with their practical implications for patient care.

CHAPTER II

SYSTEMATIC LITERATURE REVIEW

Introduction

The international crisis of emergency department (ED) crowding has received considerable attention, both in political [4,12] and lay [37-41] venues. In 1986 the Emergency Medical Treatment and Active Labor Act (EMTALA) mandated that all patients who present to an ED in the United States must receive a medical screening examination, regardless of their ability to pay [5]. The unique role of the ED has prompted some to call it the safety net of the health care system [2,42]. Unfortunately, the increasing problem of crowding has strained this safety net to the "breaking point" according to a recent report by the Institute of Medicine [4,43].

Escalation of the ED crowding problem has prompted researchers to investigate a number of scientific questions, some of which have been summarized by systematic literature reviews. One review characterized the diverse ways in which researchers have defined "overcrowding" [31]. The authors found that the term has frequently been defined using various factors inside and outside of the ED and hospital. They concluded that the crowding research agenda would benefit from a consistent definition. Another review characterized ambulance diversion, whereby an ED advises ambulances to transport patients to other nearby hospitals when possible [44]. The authors found that ambulance diversion is a frequent reaction to ED crowding, which may carry consequences including delayed patient transport and lost hospital revenue.

As noted by the Institute of Medicine, understanding the causes, effects, and solutions of the ED crowding problem is important. However, to the best of our knowledge, no previous systematic literature review has summarized this research. The objective of this review was to describe the scientific literature on ED crowding from the perspective of causes, effects, and solutions.

Methods

Search Strategy

We defined the scope of this review to include articles that, as a primary objective, studied causes, effects, or solutions to ED crowding. We adopted the definition of the word "crowding" proposed by the American College of Emergency Physicians [20]: "Crowding occurs when the identified need for emergency services exceeds available resources for patient care in the emergency department, hospital, or both." From this definition, we interpreted crowding to be a phenomenon that involves the interaction of supply and demand. Relevant articles were required to study causes, effects, or solutions of ED crowding on an empirical basis, implying that the data collection and analysis methodology must be described. Relevant articles were also required to study everyday crowding in a general ED setting, reflecting our focus on daily surge rather than exceptional circumstances. We did not consider articles that studied crowding in the context of specialty services, like psychiatric emergency medicine. We also did not consider articles that studied crowding in the context of disaster events.

We identified a broad set of PubMed® (MEDLINE®) search terms to encompass each facet of the inclusion criteria. The search involved free text and Medical Subject Headings (MeSH®) terms. We described the concept of "emergency department" by the following search terms: Emergency Medical Services[MeSH] OR Emergency Medicine[MeSH] OR "emergency". We described the concept of "crowding" by the following search terms: Crowding[MeSH] OR "crowding" OR "crowded" OR "overcrowding" OR "overcrowded" OR "diversion" OR "divert" OR "congestion" OR "surge" OR "capacity" OR "crisis" OR "crises" OR "occupancy". We queried MEDLINE on June 6, 2006 using the Boolean union of the above queries, restricting the search to English language publications.

Study Selection

Two reviewers independently examined the results returned by the MEDLINE search to identify potentially relevant abstracts. Articles that clearly did not meet the review criteria based on the title and abstract were not considered further. When the two reviewers disagreed, a consensus was reached through discussion. We retrieved full-text articles for the potentially relevant abstracts. The same two reviewers independently examined the full-text articles to determine which studies met the inclusion criteria. Disagreements were again resolved through discussion to reach a final consensus set of articles that met the review criteria.

Assessment of Study Quality

To assess the methodological quality of the studies, we applied an adapted version of a previously described five-level instrument [45]. Quality level 1 included prospective studies that studied a clearly defined outcome measure using a random or consecutive sample that was large enough to achieve narrow confidence intervals and diverse enough to suggest generalizability of the findings. Quality level 2 included prospective studies that were more limited in terms of sample size or generalizability. Quality level 3 included retrospective studies that otherwise would have satisfied the criteria for quality levels 1 or 2. Quality level 4 included studies that sampled by convenience or other techniques that were prone to introduce bias. Quality level 5 included studies that lacked a clearly defined or validated outcome measure. We did not score articles that lacked necessary methodological details for the quality instrument.

We applied the above study quality instrument consistently to clinical trials, descriptive studies, and surveys: Regardless of whether an intervention was conducted, each study was judged primarily based on 1) whether the outcome of interest occurred before or after the initiation of the study protocol, 2) the degree to which the sampling methodology applied was unbiased, and 3) the justification provided for the chosen outcome measure in the study.

Data Collection and Processing

We used a data extraction form to record information about the methods and results of each relevant article, including 1) study design, 2) study setting, 3) study population, 4) sample size, 5) independent variables, 6) dependent variables, and 7) primary findings. We assigned the articles to non-exclusive groups according to whether they investigated causes, effects, or solutions of ED crowding. We attempted to represent the intentions of the original authors when assigning each article to a group. For example, an issue such as ambulance diversion may be considered a cause, effect, or solution of ED crowding depending on the perspective of each individual study – it might be a cause of crowding at nearby institutions to which patients are diverted; it might be an effect of crowding at a single institution of interest; or it might be a solution of crowding by reducing the patient load. Within the groups representing causes, effects and solutions of ED crowding, we further categorized articles according to common themes that emerged among the primary findings during the data abstraction phase.

Results

The MEDLINE query returned 4,271 abstracts. The reviewers identified 188 abstracts for full-text retrieval, of which 93 articles satisfied the criteria for inclusion in the review. A flow diagram of the selection process is presented in figure 3. The rate of reviewer agreement prior to consensus discussion was 93% overall, 76% among included articles, and 94% among excluded articles. The kappa statistic for chance-corrected agreement between the two reviewers was 0.47 (95% confidence interval: 0.42, 0.52), denoting moderate agreement [46].

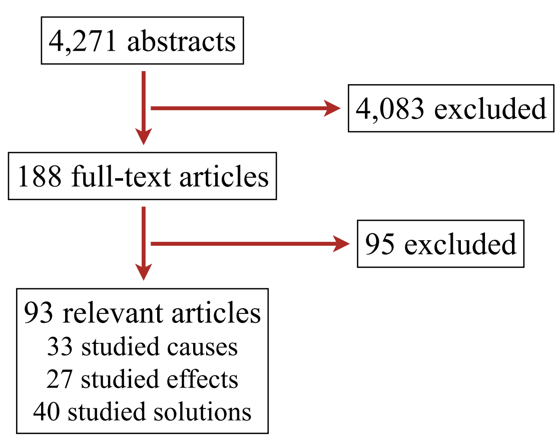

Figure 3. Flow chart of the study selection process. Articles were defined to be relevant if they 1) studied causes, effects, or solutions of ED crowding as a primary objective; 2) provided a description of the data collection and analysis; 3) took place in a general adult or pediatric ED setting; and 4) focused on everyday crowding instead of disaster-related crowding. Both phases of study selection involved a consensus between two independent reviewers.

Table 1. Methods and results of each high-quality prospective study

Article	Focus	Design	Sample	Outcome measures	Primary findings
Quality level 1					
Andersson, 2001 [57]	cause	prospective observational	16,246 patients	waiting time, ED length of stay	ED visits increased from 247.8 to 287.7 per 1000 population, waiting time increased by 8.2 minutes for non-referred patients
Bayley, 2005 [97]	effect	prospective cohort	904 patients	marginal cost	825 patients boarded more than 3 hours, opportunity cost of $204 per boarding patient, annual total of $168,300 for hospital
Burt, 2006 [91]	effect	survey	405 EDs	ambulance diversion	16.2 million ambulance transports in United States, 501,000 diversion events annually, 70% from large EDs, 85% response rate
Eckstein, 2004 [99]	effect	prospective observational	21,240 incidents of out-of-service	time to unload patient	1 in 8 transports took at least 15 minutes to unload patient, increasing over time, more frequent from January to March
Fromm, 1993 [67]	cause	prospective cohort	17,900 visits	ED length of stay	8.5% of ED patients were critically ill, remained in ED for 145.3 minutes; 154 patient-days of critical care were administered
Haines, 2006 [122]	solution	prospective case series	704 incidents of non-transport	hospital admission rate, patient satisfaction	paramedic decision to not transport pediatric patients led to a 2.4% admission rate, no deaths, good patient satisfaction
Lambe, 2003 [60]	cause	prospective observational	1798 patients	waiting time	waiting times averaged 56 minutes, each $10,000 decrease in local per-capita income increased waiting times by 10.1 minutes
Neely, 1994 [83]	effect	prospective observational	481 patients	transport distance, time	diverted patients traveled 5.0 to 11.6 minutes longer and 1.3 to 4.6 miles further than non-diverted patients
Patel, 2006 [118]	solution	before-after intervention	3 years	ambulance diversion	community-wide diversion policy decreased diversion hours by 74%, despite increases of 6.5% in census and 8.8% in admissions
Shah, 2006 [121]	solution	before-after intervention	2 months	ambulance diversion	destination-control program reduced diversion by 41% at a university hospital and 61% at a community hospital
Shaw, 1998 [103]	solution	before-after intervention	48,669 children	elopement, waiting time	additional personnel called on 32% of days, waiting time decreased by 15 minutes, elopement rate decreased by 37%
Solberg, 2003 [23]	solution	Delphi method	74 experts	magnitude estimation	38 consensus measures of patient demand and complexity; ED capacity, efficiency, and workload; hospital efficiency and capacity

Table 1, continued. Methods and results of each high-quality prospective study

Article	Focus	Design	Sample	Outcome measures	Primary findings
Quality level 1					
Vilke, 2004 [119]	solution	before-after intervention	2 years	ambulance diversion	standardized diversion guidelines reduced diversion hours from 4,007 to 1,079 and diverted patients from 1,320 to 322
Weiss, 2004 [26]	solution	prospective observational	336 observations	staff assessments of crowding	NEDOCS predicted crowding assessments with R-squared of 0.49, reduced model retained 88% of accuracy
Quality level 2					
Baker, 1991 [94]	effect	prospective cohort	397 patients	triage assessment, self-reported health status, hospitalization	46% of patients who left without being seen needed immediate medical attention, 11% were hospitalized in the next week
Bindman, 1991 [96]	effect	prospective cohort	700 patients	waiting time, self-reported health status	15% of patients left without being seen, 86% due to waiting time, doubled risk of worse pain or disease severity
Bucheli, 2004 [101]	solution	before-after intervention	360 patients	ED length of stay	additional physician during evening shift decreased length of stay from 176 ± 137 to 141 ± 86 minutes for outpatients
Fatovich, 2003 [58]	cause	prospective observational	141 incidents of diversion	reason for ambulance diversion	30.4% of ambulance diversion incidents caused by entry block, 13.6% by access block, 27.2% by both, 15.2% by high acuity
Grumbach, 1993 [47]	cause, solution	survey	700 patients	reason for visit, willingness to seek alternate care	45% of patients cited barriers to primary care, 13% had urgent complaints, 38% would trade visit for primary care appointment
Kelen, 2001 [105]	solution	before-after intervention	12 weeks	elopement, ambulance diversion	acute care unit decreased patient elopement from 10.1% to 5.0% and ambulance diversion from 6.7 to 2.8 hours per 100 patients
Michelen, 2006 [123]	solution	before-after intervention	711 patients	ED utilization	frequent-flyer patients decreased ED usage after primary care referral, health education, and counseling, $p < 0.01$ for each
Raj, 2006 [126]	solution	prospective observational	128 observations	staff assessments of crowding	mean difference of 3.47 between NEDOCS and staff assessments, 95% agreement limits of -46.52 to 53.43
Reeder, 2003 [25]	solution	prospective observational	221 observations	staff assessments of crowding	READI bed ratio differed by 0.245, acuity ratio by 0.131 between periods of normal and excess demand

Table 1, continued. Methods and results of each high-quality prospective study

Article	Focus	Design	Sample	Outcome measures	Primary findings
Quality level 2					
Schneider, 2003 [61]	cause, effect	survey	250 EDs	operating status at index time	4.2 patients per nurse, 9.7 patients per physician, 11% of EDs diverting, and 22% of patients boarding, 36% response rate
Vilke, 2004 [117]	solution	before-after intervention	3 weeks	ambulance diversion	frequency of ambulance diversion decreased from 27.7 to 0 hours when nearby hospital stopped diverting ambulances
Washington, 2002 [112]	solution	randomized controlled	156 patients	self-reported health status, care utilization	patients with three symptom complexes deferred to next-day care had similar health status and care utilization at follow-up

We found that quality level 1 contained 14 articles, quality level 2 contained 12 articles, quality level 3 contained 47 articles, quality level 4 contained 10 articles, and quality level 5 contained 6 articles. Four articles were not scored due to inadequate reporting of methodology. The primary findings of all articles are summarized briefly in the following sections. The methods and results of each high-quality prospective study are described in table 1. A total of 33 articles studied causes, 27 articles studied effects, and 40 articles studied solutions of ED crowding. This sum exceeds 93 because some articles were assigned to multiple categories as necessary.

Causes

Three general themes existed among the causes of ED crowding: input factors, throughput factors, and output factors. These themes correspond to a conceptual framework for studying ED crowding [22]. Input factors reflected sources and aspects of patient inflow. Throughput factors reflected bottlenecks within the ED. Output factors reflected bottlenecks in other parts of the health care system that might affect the ED. The commonly studied causes of crowding are summarized in table 2.

Table 2. Commonly studied causes of ED crowding

Cause of crowding	References
Input factors	
Non-urgent visits	47-50
Frequent-flyer patients	51,53
Influenza season	54-56
Throughput factors	
Inadequate staffing	60-62
Output factors	
Inpatient boarding	16,61-62,66-67
Hospital bed shortages	68-73

Input factors. We identified non-urgent visits, frequent-flyer patients, and the influenza season to be commonly studied input factors that may cause crowding.

Four articles considered non-urgent visits: Three studies found that low-acuity ED patients frequently sought non-urgent care in the ED, and their reasons for doing so included insufficient or untimely access to primary care [47-49]. However, one analysis suggested that visits by patients with non-urgent complaints were not associated with the most severe crowding at large hospitals [50].

Two articles studied frequent-flyer patients: One report found that frequent visitors, defined by four or more annual visits, accounted for 14% of the total ED visits [51]. Moreover, these patients generally did not have urgent complaints and exhibited Andersen's "need factors" for health care [52]. A similar report found that the 500 most frequent users of one ED accounted for 8% of total visits, and 29% of these visits might have been appropriate for primary care [53].

Three articles investigated the influenza season: Los Angeles County hospitals recorded a four-to-seven fold increase in ambulance diversion during the peak four weeks of flu season, as compared to other times of the year [54]. In Toronto, every 10 local cases of flu resulted in a 1.5% increase in the fraction of ED visitors who were elderly flu patients [55]. The same group in Toronto calculated that every 100 local cases of flu resulted in an increase of 2.5 hours per week of ambulance diversion [56].

Four articles examined other aspects of input factors: Stockholm experienced a 21% increase in ED visits over a four-year span, far exceeding the population growth of 4.5% during the same period; the authors attributed this to two hospital closures that caused the ED to become more responsible for primary care delivery [57]. One study estimated that excess patient volume prompted 71% of ambulance diversion episodes, and excess patient acuity prompted 15% of ambulance diversion episodes [58]. Although recently discharged inpatients accounted for just 3% of total visits to one ED, they had longer lengths of stay and more frequent hospital admissions than other patients [59]. California EDs that were located in neighborhoods of lower socioeconomic status had increased waiting times, estimated to be 10 minutes longer per $10,000 reduction in per capita income [60].

Throughput factors. We identified inadequate staffing to be a commonly studied throughput factor that may cause crowding.

Three articles discussed inadequate staffing: A point prevalence study of crowding found that the average nurse was caring for 4 patients simultaneously, and the average physician was caring for 10 patients simultaneously [61]. A study in California showed that lower staffing levels of physicians and triage nurses predisposed patients to wait longer for care [60]. By contrast, a time series analysis indicated that, after controlling for other factors, ambulance diversion was not associated with physician and nurse staffing levels [62].

Three articles discussed other aspects of throughput factors: During a nine-year period, the number of California EDs decreased by 12% while the number of ED beds increased by 16% [63]. This may not have been sufficient considering that the number of visits and critical visits per ED increased by 27% and 59%, respectively, during the same period. The training background of the attending in charge of an ED has been independently associated with patients leaving without being seen [64]. The use of ancillary services, including computed tomography (CT) scanning and other procedures, prolonged the ED length of stay among surgical critical care patients [65].

Output factors. We identified inpatient boarding and hospital bed shortages to be commonly studied output factors that may cause crowding.

Five articles studied inpatient boarding: One study found that half of EDs in the United States reported extending boarding times for patients in the ED [66]. A point prevalence study found that 22% of all ED patients were boarding at one time [61]. One academic ED delivered 154 patient-days of care to critically ill patients over a one-year period [67]. Patients experiencing access block, defined by boarding time exceeding eight hours, was associated with increased diversion, waiting times, and occupancy level in an Australian ED [16]. A time series analysis showed that the number of boarding patients was independently associated with the frequency of ambulance diversion [62].

Six articles examined hospital bed shortages: A study of English accident and emergency trusts found a strong correlation between ED treatment time and hospital occupancy [68]. A period of widespread hospital restructuring in Toronto independently increased the rate of severe overcrowding from 0.5% to 6% [69]. Length of stay in one ED increased substantially when the hospital occupancy levels exceeded 90% [70]. A survey of Korean EDs linked high hospital occupancy levels to ED crowding [71]. A study in Portland found that a decrease in hospital beds was strongly associated with an increase in ambulance diversion [72]. Another study estimated that a hospital closure would affect the nearest ED by increasing ambulance diversion by 56 hours per month for four months [73].

Additional themes. Five surveys and interviews identified factors that health care providers and other stakeholders perceive to be important causes of ED crowding: increasing patient volume and acuity, shortages of treatment areas, shortages of nursing staff, delays in ancillary services, boarding inpatients, and hospital bed shortages [74-78].

Effects

Four general themes existed among the effects of ED crowding: adverse outcomes, reduced quality, and impaired access, and provider losses. Adverse outcomes reflected health-related patient endpoints. Reduced quality reflected benchmarks of the care delivery process. Impaired access reflected the ability of patients to receive timely care at their preferred institutions. Provider losses reflected consequences borne by the health care system itself. The commonly studied effects of crowding are summarized in table 3.

Adverse outcomes. We identified patient mortality to be a commonly studied adverse outcome of crowding.

Four articles focused on patient mortality: One study found a significant increase in mortality associated with weekly ED volume [79]. High occupancy in one Australian ED was esti-

Table 3. Commonly studied effects of ED crowding

Effect of crowding	References
Adverse outcomes	
Patient mortality	79-82
Reduced quality	
Transport delays	83-86
Treatment delays	87-90
Impaired access	
Ambulance diversion	61,91
Patient elopement	64,92-96
Provider losses	
Financial impact	97-98

mated to cause 13 patient deaths per year [80]. Another study associated a combined measure of hospital and ED crowding with an increased risk of mortality at 2, 7, and 30 days following hospital admission [81]. In Houston, a statistically insignificant trend was found for higher mortality among trauma patients who were admitted during ambulance diversion [82].

Reduced quality. We identified transport delays and treatment delays to be commonly studied effects of crowding pertaining to reduced quality.

Four articles examined transport delays: Ambulance diversion was shown to increase transport time and distance in two studies [83-84]. A study focused on cardiac patients found that the 90th percentile of transport time increased when multiple local hospitals were on diversion [85]. During two years in which crowding was exacerbated in Toronto, the 90th percentile of transport time increased by 11% [86].

Four articles investigated treatment delays: Patients who arrived at one ED during crowded periods waited 30 minutes longer for an ED bed [87]. Crowding was associated with increased door-to-needle time for patients with suspected myocardial infarction [88]. High ED occupancy levels were associated with delayed pain assessment and lower likelihood of pain documentation among hip fracture patients [89]. A negative trial found no increase in the time to head computed tomography among suspected stroke patients when a trauma evaluation occurred simultaneously [90].

Impaired access. We identified ambulance diversion and patient elopement to be commonly studied effects of crowding pertaining to impaired access.

Two articles focused on ambulance diversion: A national survey found that approximately 501,000 ambulance diversions occurred in the United States during one year, and approximately 70% of these were from large EDs [91]. A point prevalence study of ED crowding found that 11% of United States EDs were simultaneously diverting ambulances [61].

Six articles characterized patient elopement: Patients were more likely to leave without being seen when ED occupancy exceeded 100% of the total capacity [64]. In one study, the rate of patients leaving without being seen closely correlated with waiting times [92]. The rate of patients leaving one ED without being seen correlated well with a crowding regression model [93]. Among patients who left without being seen, 46% needed urgent medical attention, and 11% were hospitalized within a week [94]. Patients frequently cited long waiting times as a reason for leaving without being seen, and 60% of them sought other medical care within a week [95]. Patients who left the ED without being seen were twice as likely to report worsened health problems [96].

Provider losses. We identified financial impact to be a commonly studied provider loss of crowding.

Two articles calculated financial impact: One study estimated that the hospital lost $204 in potential revenue per patient with an extended boarding time [97]. Another study found that patients who boarded in the ED longer than a day also stayed in the hospital longer, increasing costs by an estimated $6.8 million over three years [98].

Two articles considered other aspects of provider losses: A study found that during one in eight patient transports, the ambulance could not unload the patient promptly at the ED, putting it out of service for 15 minutes or more [99]. A survey of Canadian emergency physicians found that job dissatisfaction was closely related to the perceived scarcity of resources [100].

Additional themes. Three surveys identified outcomes that ED directors perceive to be major effects of crowding: death, delayed care, unnecessary procedures, and extended pain [74-76].

Solutions

Three general themes existed among the solutions of ED crowding: increased resources, demand management, and operations research. Increased resources reflected the deployment of additional physical, personnel, and supporting resources. Demand management reflected methods to redistribute patients or encourage appropriate utilization. Operations research reflected crowding measures and offline change management techniques. The commonly studied solutions of crowding are summarized in table 4.

Table 4. Commonly studied solutions of ED crowding

Solution of crowding	References
Increased resources	
Additional personnel	101-103
Observation units	104-107
Hospital bed access	108-109
Demand management	
Non-urgent referrals	47,112-114
Ambulance diversion	115-119
Destination control	120-121
Operations research	
Crowding measures	23-26,28,125-127
Queuing theory	34-35

Increased resources. We identified additional personnel, observation units, and hospital bed access to be commonly studied solutions of crowding involving increased resources.

Three articles studied additional personnel: One described a permanent increase in the number of physicians during a busy shift, reducing the outpatient length of stay by 35 minutes [101]. A rural hospital, which previously did not have an attending physician present during the night shift, found that the presence of an attending physician improved several throughput measures of ED crowding [102]. One hospital activated reserve personnel on an as-needed basis during the viral epidemic season, reducing the waiting time by 15 minutes and the rate of patients leaving without being seen by 37% [103].

Four articles investigated observation units: One short-stay medicine unit reduced the length of stay for outpatients with chest pain and asthma exacerbation [104]. Another study found that an ED-managed acute care unit decreased ambulance diversion by 40% and halved the rate of patients leaving without being seen [105]. A hospital reported that the addition of an acute medical unit reduced the median number of boarding patients from 14 to 8 over a 2-year period [106]. One study proposed a hybrid observation unit, which was designed to use resources effectively and substantially decreased the length of stay for scheduled procedure patients [107].

Two articles considered hospital bed access: After increasing the number of critical care beds from 47 to 67, ambulance diversion at one hospital decreased by 66% [108]. A natural experiment resulting from a period of industrial action, leading to improved hospital bed access for an ED, resulted in significant decreases in occupancy levels and waiting times [109].

Two articles examined other aspects of increased resources: One study increased both space and staffing through an ED reorganization, which resulted in the improvement of several crowding outcomes [110]. Another study attempted to reduce the potential bottleneck of ancillary services by implementing point-of-care laboratory testing, which decreased the length of stay by 41 minutes [111].

Demand management. We identified non-urgent referrals, ambulance diversion, and destination control to be commonly studied solutions of crowding involving demand management.

Four studies tested non-urgent referrals: A survey of ED patients found that 38% would swap their ED visit for a primary care appointment within 72 hours [47]. A randomized, controlled trial focused on three common symptom complexes and found that they may be deferred for next-day primary care without worsening self-reported health status on follow-up [112]. When following up non-urgent patients who were triaged to receive care elsewhere, one group found that there were no major adverse outcomes, and 42% of the patients received same-day care elsewhere [113]. A similar study found that 94% of non-urgent patients who were referred to community-based care reported that their condition was better or unchanged [114].

Five studies investigated ambulance diversion: By one calculation, ambulance diversion decreased the rate of ambulance arrivals by 30% to 50% [115]. A similar calculation found that "red-alert" ambulance diversion reduced the arrival rate by 0.4 per hour [116]. When one hospital committed to avoiding ambulance diversion for one week, the need for diversion at a nearby hospital was almost eliminated [117]. Standardized diversion criteria in Sacramento, targeted to decrease “round-robin” crowding, reduced the rate of ambulance diversion by 74% in spite of increased patient volume [118]. San Diego implemented a standardized policy for initiating ambulance diversion among all local hospitals and reduced ambulance diversion by 75% [119].

Two studies proposed destination control: The use of Internet-accessible operating information to redistribute ambulances reduced the need for diversion from 1788 hours to 1138 hours in one network [120]. Another study described a physician-directed ambulance destination control initiative that reduced diversion by 41% [121].

Three studies considered other aspects of demand management: A trial of paramedic-initiated non-transport found that 2.4% of non-transported pediatric patients were later admitted to the hospital [122]. Three social interventions designed for frequent visitors, which included education and counseling, were associated with decreased ED utilization [123]. Another study targeted frequent users with case management interventions, but the rate of ED utilization was unchanged [124].

Operations research. The studies within the operations research theme did not describe direct solutions to ED crowding; however, they proposed to support solutions through improved business intelligence. We identified crowding measures and queuing theory to be commonly studied solutions to crowding based on operations research.

Eight studies described crowding measures: The Emergency Department Work Index (EDWIN) associated well with ambulance diversion and less well with secondary outcome measures at its institution of origin [24]. The National Emergency Department Overcrowding Scale (NEDOCS) explained 49% of the variation in physician and nurse assessments of crowding [26]. The Real-time Emergency Analysis of Demand Indicators (READI) were designed for real-time monitoring of ED operations, although they did not correlate with providers' opinions on crowding [25]. The Work Score predicted ambulance diversion at its institution of origin with area under the receiver operating characteristic curve (AUC) of 0.89 [28]. A comparative validation, which employed staff assessments of crowding as the outcome, estimated the AUC of the EDWIN to be 0.80 and of the NEDOCS to be 0.83 [125]. However, an external validation of the NEDOCS in Australia concluded that it was not useful, based on Bland-Altman and kappa statistics [126]. A sampling form consisting of seven operational measures was shown to correlate well with staff assessments of crowding [127]. A panel of experts described 38 consensus operational measures that may be used to assess crowding levels [23].

Two studies employed queuing theory: One group illustrated the ability of discrete event simulation to model ED operations, and they tested its applicability by analyzing a proposed triage scheme [34]. A similar study described a separate discrete event simulation and studied the effects of physician utilization on patient waiting times [35].

Additional themes. Five studies described multi-faceted administrative interventions that could not be classified separately: A broad intervention consisting of 51 actions reduced ED length of stay and ambulance diversion in Melbourne [128]. One network deployed several interventions, tuned for the individual needs of four hospitals, and reduced the amount of ambulance diversion by 25% and 34% in consecutive years [129]. A group of hospitals in Rochester deployed several interventions, and they reported that the most effective interventions occurred outside the ED [130]. Another study reported interventions, including more physicians, improved ancillary services, and changes in hospital policy, that reduced length of stay by half [131]. One hospital deployed a multi-pronged intervention, which involved a short-stay unit, additional physicians, and an early warning system, to deal with holiday demand surges [132].

Limitations

This study has a number of limitations that merit discussion. First, we may not have captured every article that studied causes, effects, and solutions of ED crowding. We limited the search to English-language articles, so any relevant articles published in foreign languages were not included. We searched a single database; moreover, it is possible that our search terms did not capture all aspects of the topic. The MeSH vocabulary contains a single term related to crowding, so we supplemented the search with a large set of free text keywords. We attempted to minimize the likelihood of missed articles by applying a broad search strategy. We also used a conservative approach during the abstract screening phase, retrieving the full-text articles for all abstracts that could not be clearly excluded. We believe this approach captured the substantial majority of pertinent articles.

Second, we attempted to describe the primary findings of each study as consistently as possible; however, this was not always practical given the diversity of methodology, outcome measures, and reporting among the original articles. We noted the effect sizes of each study when feasible, and in other cases we described the nature of the findings in more qualitative terms. The brief summaries that we provide do not capture the full complexity of each study, so our review is intended to guide interested readers to the original cited articles.

Third, the classification of studies into groups and themes was partly subjective, so objections may be made regarding how particular articles were categorized. We acknowledge that there may be no clearly correct taxonomy for grouping this diverse set of articles; our intention in doing so was to provide a structured overview of the relevant literature, which we hope benefits the reader.

Discussion

A substantial body of literature exists describing the causes, effects, and solutions of ED crowding. The major themes among the causes of crowding included non-urgent visits, frequent-flyer patients, influenza season, inadequate staffing, inpatient boarding, and hospital bed shortages. The major themes among the effects of crowding included patient mortality, transport delays, treatment delays, ambulance diversion, patient elopement, and financial impact. The major themes among the solutions of crowding included additional personnel, observation units, hospital bed access, non-urgent referrals, ambulance diversion, destination control, crowding measures, and queuing theory.

The quality instrument that we employed indicated that a large number of high-quality articles have been published regarding ED crowding [45]. We identified a total of 26 prospective studies and 47 retrospective studies that met the criteria for the three highest quality levels. We noted a scarcity of randomized controlled trials in this review, perhaps because many ED operational changes involve the entire department, rather than individual patients who may be randomized to experimental and control groups [112].

While understanding the problem of ED crowding is valuable, the ultimate purpose of this research is to alleviate the problem. It is possible that lasting, widespread alleviation of the problem will require sweeping change involving all aspects of our medical culture [4,12,133]. While remaining hopeful for such change, however, EDs remain responsible to maintain patient safety and access despite unfavorable conditions. In light of this, we offer two observations that may benefit the solution-oriented literature. First, many of the intervention studies in this review considered intermediate outcome measures, including waiting times, occupancy level, and length of stay. Crowding research may benefit from a greater focus on patient-oriented outcome measures, such as patient mortality, adverse events, or health status on follow-up. Second, few studies demonstrated the feasibility of deploying additional resources on demand [103]. A result of queuing theory states that a system with stochastic inputs and fixed capacity will become congested for transient periods of time [21]. By consequence, permanent increases in resources may be neither efficient nor adequate to address crowding; rather, a better approach may involve dynamically mobilizing resources to match the fluctuating demand.

When considered as a whole, the body of literature demonstrates that ED crowding is a local manifestation of a systemic disease. The causes of ED crowding involve a complex network of interwoven processes ranging from patient attitudes to hospital workflow. The effects of ED crowding are numerous and, in some cases, deadly. Various targeted solutions to crowding have been shown to be effective, and further studies may demonstrate new innovations. This broad overview of the current research may help to inform the future research agenda and, subsequently, to protect the fragile safety net of the health care system.

CHAPTER III

CROWDING MEASURES

Introduction

Background

Emergency department (ED) crowding is recognized to be a major, international concern that affects both patients and providers [2,61,66,75,134-139]. A recent report from the Institute of Medicine noted that the increasing strain caused by crowding is creating a deficit in quality of emergency care [4]. Crowding has been associated with reduced access to emergency medical services [16,64,94-95], delays in care for cardiac patients [85-86,88], increased patient mortality [79-82], extended patient transport time [84,99], inadequate pain management [89], violence of angry patients against staff [140], increased costs of patient care [98], and decreased physician job satisfaction [100].

Importance

As suggested by the principle "you can't manage what you can't measure," the lack of a universal metric for ED crowding impedes efforts to alleviate the problem [23,31]. In an effort to address this, mathematical formulas have been proposed in the peer-reviewed literature to quantify crowding: the Emergency Department Work Index (EDWIN), the National Emergency Department Overcrowding Scale (NEDOCS), the Demand Value of the Real-time Emergency Analysis of Demand Indicators (READI), and the Work Score [24-26,28,141]. These four measures use simple operational variables to assess the present state of crowding in an ED.

There have been mixed reports in the literature about the usefulness of these measures to assess ED crowding [24-26,28,93,125,141-144]. Prior validation efforts have often used subjective assessments of crowding by physicians and nurses as the dependent variable [24-26,125, 144]. The measures were intended for continuous monitoring of ED operations [24-26,28,141]; however, only the Work Score has been integrated with a clinical information system [28]. Furthermore, the measures have the potential to serve as an early warning system for overcrowding [24,28]. This capability, however, has not yet been established for any of the measures.

Goals of this Investigation

The objective of this study was to assess the usefulness of the EDWIN, the NEDOCS, the READI Demand Value, and the Work Score as monitoring instruments of ED crowding. To achieve this goal, we addressed three related questions. First, is it feasible to evaluate the measures in real time? Second, how accurately do the measures reflect present crowding? Finally, can the measures reliably forecast the future state of crowding?

Methods

Study Design

This was a prospective validation of four ED crowding measures during an eight-week period (6/21/2006 – 8/16/2006). The study did not involve any direct patient contact, and the local Institutional Review Board approved the study by expedited review.

Setting

The validation took place in the adult ED of a tertiary-care, academic medical center with a Level 1 trauma service. The adult ED provides care for more than 45,000 patients annually. It contains 41 licensed beds, four of which are trauma beds. In addition, four fast-track beds are available for low-acuity patients from 11 AM to 11 PM, and eight dedicated rooms are available for psychiatric patients. The ED staff were kept unaware of the study to avoid a potential source of bias. The validation site was independent of the development site for all measures considered.

Methods of Measurement

The EDWIN, the NEDOCS, the READI Demand Value, and the Work Score were calculated to assess the degree of crowding [24-26,28,141]. All four of these measures output a continuous variable, where a higher value denotes a greater degree of crowding.

The EDWIN [24] was calculated using the following formula:

$$EDWIN = \sum n_i t_i / (N_a * (B_t - P_{board}))$$

where n_i = number of non-boarding patients in triage category i; t_i = reversed triage category i, where 5 denotes the sickest patients and 1 denotes the least sick patients; N_a = number of attending physicians on duty; B_t = number of licensed treatment beds in the ED; and P_{board} = number of boarding patients.

The NEDOCS [26] was calculated using the following formula:

$$NEDOCS = (P_{bed} / B_t) * 85.8 + (P_{admit} / B_h) * 600 + W_{time} * 5.64 + A_{time} * 0.93 + R_n * 13.4 - 20$$

where P_{bed} = number of patients in licensed beds and overflow locations, such as hallway beds or chairs, B_t = number of licensed treatment beds, P_{admit} = number of admitted patients, B_h = number of hospital beds, W_{time} = waiting time for the last patient put into bed, A_{time} = longest time since registration among boarding patients, and R_n = number of respirators in use, maximum of two. The respirator variable (R_n) did not generalize to the study setting, because patients ill enough to require mechanical ventilation are stabilized and transferred immediately to a critical care unit. As a surrogate, the number of trauma beds was used in place of the number of respirators.

The Demand Value of the READI score [25,141] was calculated using the following formulas:

$$DV = (BR + PR) * AR$$

$$BR = (P_{total} + A_{pred} - D_{pred}) / B_t$$

$$AR = \sum n_i t_i / P_{triage}$$

$$PR = A_{hour} / \sum PPH$$

where DV = Demand Value, BR = Bed Ratio, AR = Acuity Ratio, PR = Provider Ratio, P_{total} = number of ED patients, A_{pred} = number of predicted arrivals, D_{pred} = number of predicted departures, B_t = number of licensed treatment beds, n_i = number of patients in triage category i, t_i = reversed triage category i, P_{triage} = number of patients in the ED with an assigned triage category, A_{hour} = number of arrivals in the past hour, and PPH = average patients seen per hour for each attending physician and resident on duty. The predicted number of arrivals (A_{pred}) and departures (D_{pred}) for each hour of the day was calculated using nine months of ED data (9/1/2005 – 6/1/2006). The original READI instrument used a four-level triage system, so the five-level Emergency Severity Index (ESI) was condensed into four categories by combining the two least severe acuity levels [145]. The number of patients seen per hour was calculated for residents at each level of training and for attending physicians who saw patients without a resident, using nine months of ED data (9/1/2005 – 6/1/2006).

The Work Score [28] was calculated using the following formula:

$$\text{Work Score} = 3.23 * P_{wait} / B_t + 0.097 * \sum n_i t_i / N_n + 10.92 * P_{board} / B_t$$

where P_{wait} = number of waiting patients, B_t = number of licensed treatment beds, n_i = number of patients under evaluation in triage category i, t_i = reversed triage category i, N_n = number of nurses on duty, and P_{board} = number of boarding patients.

The ED occupancy level was used as a control measure for baseline comparison. The occupancy level was calculated using the following formula:

$$\text{Occupancy level} = 100 * P_{bed} / B_t$$

where P_{bed} = number of patients in licensed beds and overflow locations, such as hallway beds or chairs; and B_t = number of licensed treatment beds.

Under extreme operating conditions, the original published formulas for the EDWIN and the Acuity Ratio of the READI score could generate mathematical errors. If the number of boarding patients in the ED matched or exceeded the number of licensed treatment beds, the denominator of the EDWIN would become zero or negative. If there were no patients in the ED with an assigned triage category, the denominator of the Acuity Ratio would become zero. However, these conditions have never been approached in the study setting, so no changes to compensate for this were deemed necessary for the present study.

Data Collection and Processing

To enable real-time monitoring of ED operations, a computer program was developed using Matlab (version 7.1, http://www.mathworks.com) and integrated with the ED information systems. At 10-minute intervals, the program queried the information systems for the data required to evaluate the four crowding measures and the occupancy level. The resulting values were recorded in a research database.

Outcome Measure

Ambulance diversion status was used as the outcome measure for overcrowding. Policy at our hospital allows for ambulance diversion when any of the following criteria apply and are not expected to be remedied within one hour: "1) all critical care beds in the ED are occupied, patients are occupying hallway spaces, and at least 10 patients are waiting; 2) an acuity level exists that places additional patients at risk; or 3) all monitored beds within the ED are full." A committee reviews the appropriateness of all diversion episodes on a monthly basis. The hospital's aeromedical service, which is responsible for maintaining diversion records, provided log files for the study period.

Primary Data Analysis

The ability of each crowding measure to discriminate current ambulance diversion status was analyzed using receiver operating characteristic (ROC) curves [146]. An ROC curve plots sensitivity against (1 - specificity) for all possible thresholds in a binary classification task. The area under an ROC curve (AUC) represents the overall discriminatory ability of a test, where a value of 1.0 denotes perfect ability and a value of 0.5 denotes no ability. To reduce the effect of serial correlation on ROC curve estimation, each measure series was down-sampled to an observation frequency of three hours. The AUC of each measure was calculated with 95% confidence intervals (CI). Pairwise tests for significant differences of AUC were conducted between each measure and occupancy level [147]. An alpha level of 0.05 / 4 = 0.0125, with the Bonferroni correction for multiple pairwise comparisons, was used for the tests of significance. All ROC analyses were performed using the ROCKIT software tool (version 0.9.1, http://xray.bsd.uchicago.edu/krl/roc_soft.htm). The operating characteristics of each measure were calculated by fixing each measure's threshold to achieve 90% sensitivity with respect to ambulance diversion status. At this fixed threshold, each measure's specificity, predictive values, and likelihood ratios were calculated.

The ability of each crowding measure to forecast ambulance diversion status in the near future was analyzed following the Centers for Disease Control framework for evaluating biosurveillance systems [148]. Activity monitoring operating characteristic (AMOC) curves were developed to characterize the performance of early warning systems [149], and they have been previously applied to the problem of disease outbreak detection [150-151]. An AMOC curve plots timeliness scores against false alarm rates for all possible thresholds in an early warning system. The false alarm rate is generally normalized per unit time – in the present study, per week. The timeliness score may be interpreted here as the median warning time given prior to diversion, within a maximum specified time window. The time window was defined to be four hours for this study, and alarms were classified as 1) true alarms, if they occurred less than four hours before the start of a diversion episode; 2) false alarms, if they occurred more than four hours before the start of a diversion episode; or 3) redundant alarms, if they occurred during a diversion episode. Redundant alarms were not further considered, because they affect neither the timeliness nor the false alarm rate.

The standard method of generating AMOC curves would treat all false alarms as independent events, even when they occurred at consecutive 10-minute intervals [149]. From an ED operational perspective, we considered it more appropriate to treat consecutive alarms as a single, sustained alarm, since the only the first alarm would trigger an intervention. Thus, the AMOC framework was extended for the present study as follows. Each measure series was de-noised using cubic spline smoothing with the Matlab function *csaps*. A smoothing parameter of 0.99 was applied, where a value of 1.0 represents no smoothing and values below 0.95 resulted in excessive smoothing. Each sequence of consecutive alarms was counted as a single, sustained signal. However, when a trough in the smoothed signal occurred during a sustained false alarm, it was considered to be the beginning of a new false alarm, thus ensuring a monotonic relationship between the false alarm rate and timeliness. All AMOC analyses were performed using Matlab (version 7.1, http://www.mathworks.com).

Table 5. Adult ED operational variables, 6/21/2006 - 8/16/2006

Characteristic	No Diversion (n = 5,599)	Diversion (n = 2,349)
Patient Factors		
Registrations in last hour (#)	6 (3 - 8)	6 (4 - 9)
Discharges in last hour (#)	5 (3 - 8)	7 (5 - 9)
Mean acuity level (ESI)	2.57 ± 0.16	2.57 ± 0.12
Occupancy level (%)	78 (61 - 88)	96 (91 - 100)
Average length of stay (h)	5.4 (3.9 - 8.3)	8.0 (6.3 - 9.6)
Waiting patients (#)	1 (0 - 4)	11 (5 - 16)
Average waiting time (min)	11 (0 - 31)	84 (52 - 115)
Boarding patients (#)	9 (4 - 15)	20 (15 - 23)
Average boarding time (h)	5.7 (2.5 - 10.2)	10.4 (7.0 - 12.6)
Provider Factors		
Attendings on duty (#)	3.0 ± 0.9	3.5 ± 0.7
Residents on duty (#)	4.4 ± 0.5	4.7 ± 0.5
Nurses on duty (#)	13.5 ± 1.8	14.5 ± 1.5
Hospital Factors		
Medical-surgical diversion	15%	26%
Critical care diversion	4%	13%

Observations were made at 10-minute intervals during the study period. Descriptions are presented as percentages for discrete variables, mean ± SD for normally distributed continuous variables, and median (IQR) for skewed variables.

The timeliness of the four crowding measures and occupancy level were compared by fixing the threshold such that each measure triggered one, two, and three false alarms per week, which was considered the maximum number likely to be tolerated by ED personnel. False alarm rates of were examined for each measure. The timeliness prior to every diversion episode was calculated, and a paired Wilcoxon rank-sum test was used to compare the median difference in timeliness between each measure and occupancy level. The Bonferroni-corrected 95% confidence intervals, equivalent to unadjusted 98.75% confidence intervals, were calculated using R (version 2.3.1, http://www.r-project.org).

Results

Characteristics of Study Period

During the study period, a total of 7,948 10-minute intervals were observed out of 8,064 possible (98.6%). Two incidents of computer system downtime accounted for all of the missed observations. Descriptive statistics for ED operational variables during the study period are listed in table 5. A total of 37 ambulance diversion episodes occurred during the study period, lasting an average of 11.7 hours per episode. There were no episodes of citywide diversion, such that the ED was forced to end its diversion, during the study period. The ED was on ambulance diversion during 30% of the intervals observed. To illustrate the response of each measure to ED overcrowding, figure 4 shows an eight-week time series plot of each crowding measure, superimposed on episodes of ambulance diversion.

Main Results

The ROC curves for the EDWIN, the NEDOCS, the READI Demand Value, the Work Score, and occupancy level are shown in figure 5. The AUC was 0.81 for the EDWIN (95% CI: 0.77-0.85), 0.88 for the NEDOCS (95% CI: 0.85-0.91), 0.65 for the READI Demand Value (95% CI: 0.60-0.71), 0.90 for the Work Score (95% CI: 0.86-0.92), and 0.90 for occupancy level (95% CI: 0.87-0.93). Pairwise tests for differences of AUC showed that occupancy level had greater

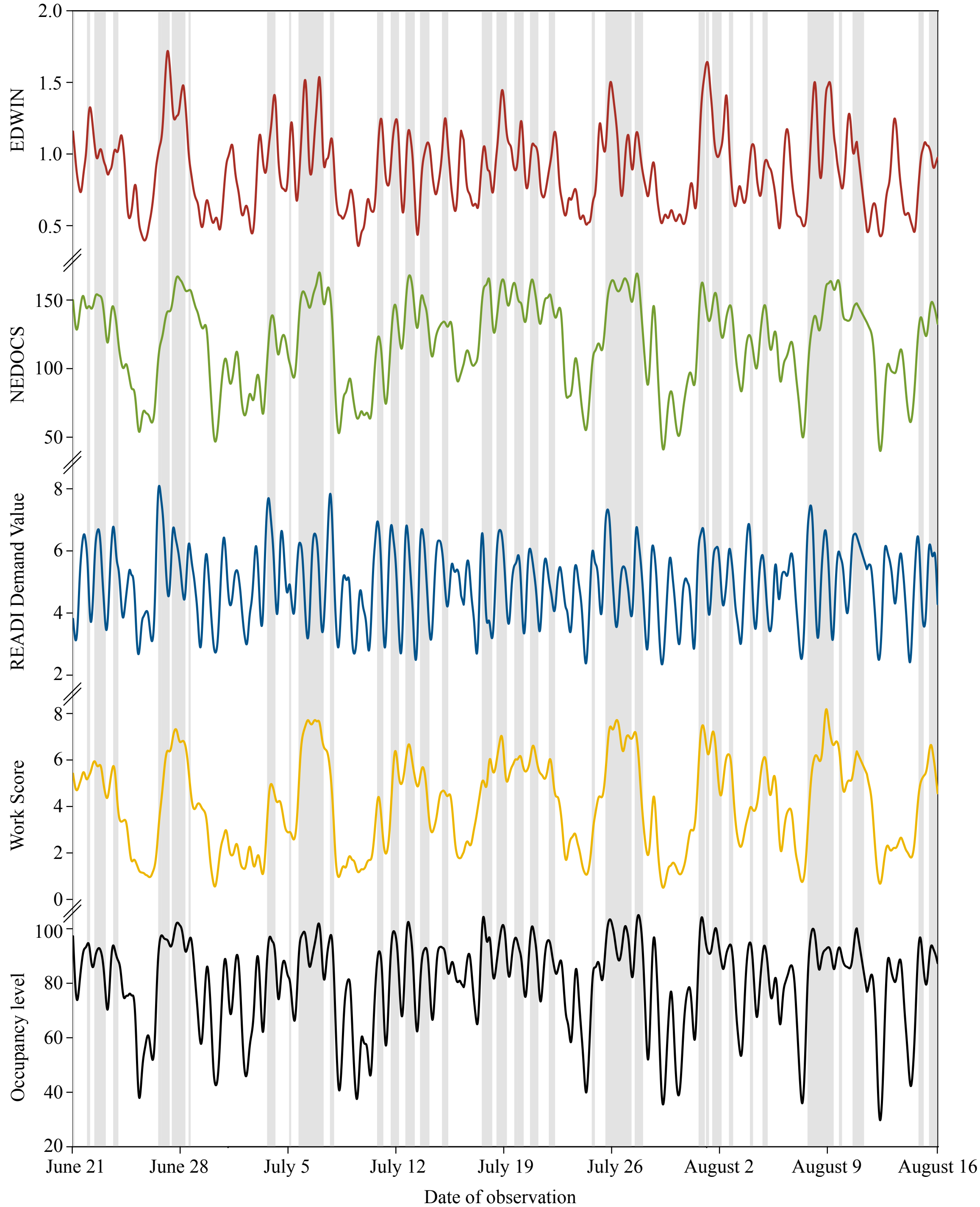

Figure 4. Time series plots of four crowding measures, 6/21/06 – 8/16/06. The plots shown here are smoothed using cubic splines. Episodes of ambulance diversion are marked by the shaded areas.

discriminatory power for overcrowding than the EDWIN ($p < 0.001$) and the READI Demand Value ($p < 0.001$), while the NEDOCS and the Work Score did not differ significantly in dis-

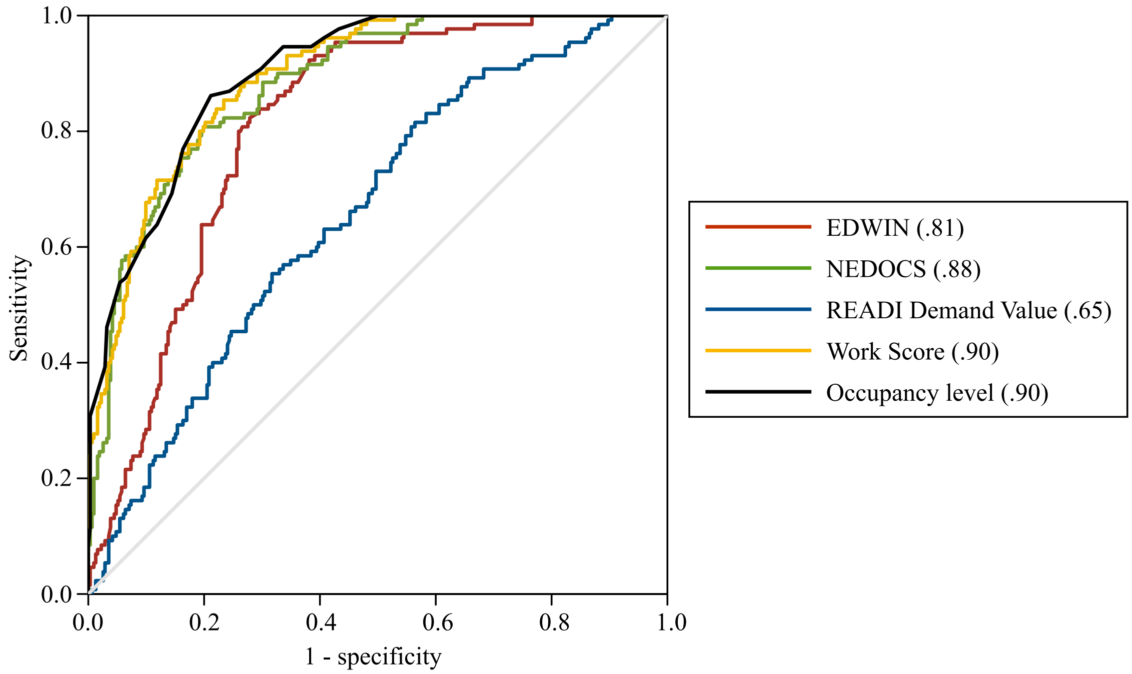

Figure 5. Receiver operating characteristic curves of four crowding measures. The AUC of each measure is shown in parentheses.

criminatory power from occupancy level (p = 0.190 and p = 0.769, respectively). The operating characteristics for each measure at a fixed sensitivity level of 90% are shown in table 6.

The AMOC curves for the EDWIN, the NEDOCS, the READI Demand Value, the Work Score, and occupancy level are shown in figure 6. Only the occupancy level provided more than

Table 6. Operating characteristics at fixed 90% sensitivity

	Spec	PPV	NPV	LR+	LR-
EDWIN	63%	50%	94%	2.42	0.15
NEDOCS	67%	53%	94%	2.75	0.15
READI Demand Value	32%	35%	88%	1.32	0.32
Work Score	71%	56%	94%	3.09	0.14
Occupancy level	70%	56%	95%	3.05	0.13

Spec = specificity; PPV = positive predictive value; NPV = negative predictive value; LR+ = positive likelihood ratio; LR- = negative likelihood ratio

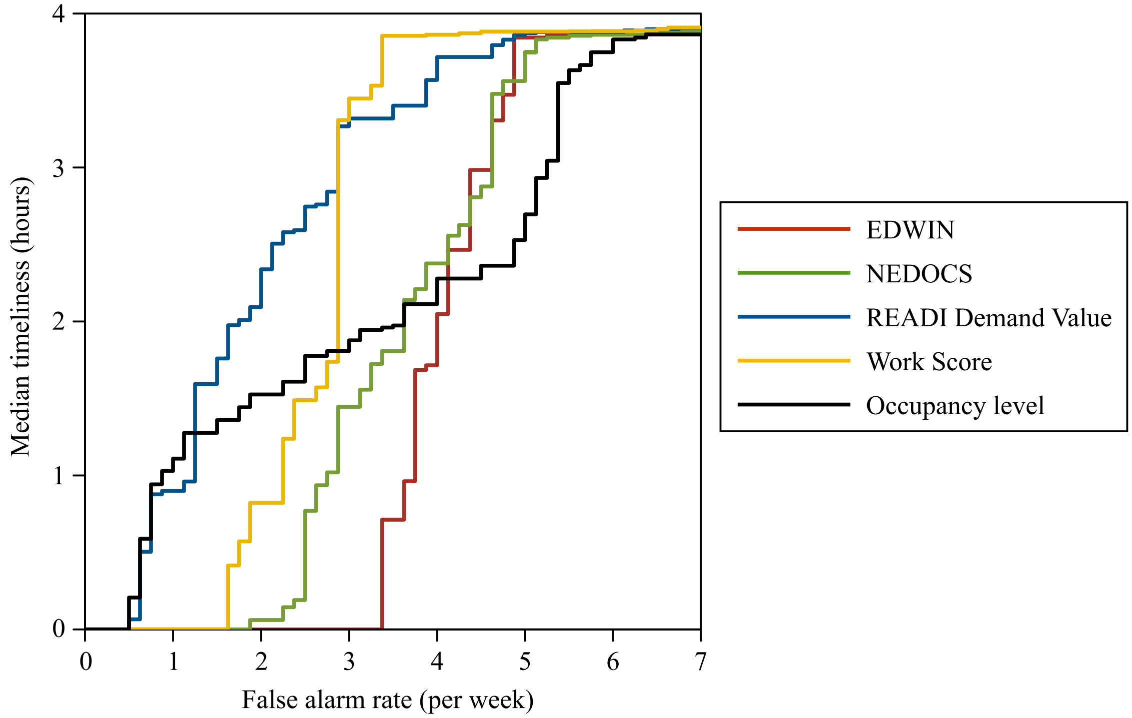

Figure 6. Activity monitoring operating characteristic curves of four crowding measures. A higher value of timeliness denotes a greater amount of warning time prior to episodes of ambulance diversion.

an hour of advance warning (median 1 hour, 7 minutes) prior to overcrowding at a rate of one false alarm per week. Note that the vertical distance between curves in figure 6 illustrates the difference between medians of timeliness; however, with non-parametric paired data, the median difference shown in table 7 may provide more reliable comparisons. As assessed by confidence

Table 7. Median difference in timeliness between crowding measures and occupancy level

	False alarm rate		
	1 per week	2 per week	3 per week
EDWIN	-1:37 (-2:48, -0:09)	-2:06 (-3:20, -0:28)	-2:01 (-2:53, -0:35)
NEDOCS	-1:04 (-2:24, 0:19)	-1:06 (-2:26, 0:27)	-0:24 (-1:56, 0:50)
READI Demand Value	0:04 (-1:16, 1:14)	0:43 (-0:50, 1:42)	1:16 (0:00, 2:05)
Work Score	-1:17 (-2:37, 0:13)	-0:20 (-1:49, 1:20)	0:02 (-1:32, 1:39)

Differences in timeliness are presented as hours:minutes. A positive value indicates that the measure gave more timely warnings than occupancy level. Lower and upper bounds of the Bonferroni-corrected 95% CI for the median difference are shown in parentheses.

intervals that do not overlap zero, the occupancy level gave more timely warnings of overcrowding than the EDWIN at rates of one, two, and three false alarms per week. When the false alarm rate was fixed at three per week, the READI Demand Value gave more timely warnings of overcrowding than occupancy level. All other pairwise comparisons of median timeliness to occupancy level were not statistically significant.

Limitations

A potential limitation of our study is the use of ambulance diversion status as a surrogate for overcrowding. While a clear, universal definition for ED overcrowding does not exist, an expert panel considered ambulance diversion status to be a practical, operational definition [152]. It has been used previously as an dependent variable to validate crowding measures [28,142-143]. The justifiability of using ambulance diversion status as an objective surrogate for overcrowding depends on the rigor of diversion policy at a given institution. As described previously, our institution has specified criteria by which ambulance diversion may be initiated, and regular reviews are conducted to ensure compliance. On these grounds, ambulance diversion status was considered to be the best available reference standard for overcrowding in this study.

A second limitation arises from the fact that the four crowding measures – the EDWIN, the NEDOCS, the READI Demand Value, and the Work Score – were originally developed for the purpose of measuring the present state of crowding [24-26,28,141]. The creators of the EDWIN and the Work Score discussed the potential use of the measures to forecast near-future overcrowding, without directly exploring this application [24,28]. As the creators of the NEDOCS and the READI did not explicitly describe this possibility, we acknowledge that validating these measures as early warning systems by AMOC analysis may have exceeded the authors' intentions [25-26,141].

Lastly, the study was conducted at a single academic institution, and further research will be required to determine the generalizability of the findings to other emergency department settings. However, as this study represents an independent, prospective validation of all four crowding measures, some notion of their generalizability may be inferred from the findings.

Discussion

The findings demonstrate that the EDWIN, the NEDOCS, the READI Demand Value, and the Work Score may be evaluated in real time by integration with ED information systems [24-26,28,141]. Implementing the four measures as monitoring instruments requires the electronic availability of common ED operational variables, such as waiting room count, length of stay, and number of boarding patients.

We examined the ability of the four measures to reflect current ED crowding. The ROC curves and operating characteristics demonstrate that the EDWIN, the NEDOCS, and the Work Score all have high discriminatory power for predicting current ambulance diversion status. However, none of the measures performed better than the control measure, occupancy level. The READI Demand Value showed lower discriminatory power, which is consistent with an earlier report that found no significant association between the READI Demand Value and staff assessments of crowding [25].

We also examined the ability of the four crowding measures to forecast near-future ED overcrowding. Based on the AMOC curves and the timeliness at fixed false alarm rates, all measures had difficulty providing much advance notice at low rates of false alarms. None of the available crowding measures clearly exceeded the control measure, occupancy level, in forecasting performance. Although the READI Demand Value showed poor discriminatory power, it performed much better in the AMOC analysis. The time series plots in figure 4 suggest that, while the other measures tend to peak in the middle of diversion episodes, the READI Demand Value appears to peak close to the beginning of diversion episodes, lending credence to its timeliness.

Two points should be noted from the analysis of forecasting power. First, it is insufficient to consider just operating characteristics such as sensitivity, specificity, and discriminatory power when validating an early warning system. Good performance in terms of discriminatory power does not imply timely forecasts, and vice versa. The Centers for Disease Control recommended a careful analysis of timeliness when evaluating public health monitoring systems [148]. Second, the READI Demand Value is the only measure evaluated that predicts near-future operational changes based on historical data. The other three measures and occupancy level are all point estimates based on current operating status. It is plausible that the use of historical data to predict near-future patient arrivals and departures explains why the READI Demand Value fares relatively well in forecasting ED crowding.

Occupancy level was intended as a simple baseline measure for comparison in the present study. It was interesting to find that none of the four crowding measures clearly exceeded its performance across the range of operating points. This finding is near in spirit to Occam's razor – roughly paraphrased, one should use the most parsimonious model possible that achieves the intended purpose, since more complex models may be prone to over-fitting.

Future efforts to validate ED crowding measures should focus on using objective endpoints to define crowding. Although not all institutions allow for ambulance diversion, researchers at any ED could define a rule involving the occupancy level, waiting room count, or other basic variables as the reference standard. The use of subjective assessment as the sole dependent variable when validating a crowding measure should be treated cautiously. For example, conflicting reports have been published regarding the utility of the NEDOCS to measure crowding, which may illustrate the difficulty of replicating findings based on a subjective dependent variable [26,125-126].

Future research should also focus on improving the forecasting power of crowding measures. The use of historical data to predict changes in the next few hours may allow for substantial improvements in the performance of an early warning system. Advanced modeling techniques such as neural networks, applied specifically for the purpose of forecasting, may result in improved forecasting power [143]. The development of a good forecasting model for ED crowding will pave the way to studying intervention policies, which may allow researchers to identify ways of sustaining health care quality and access in the face of overcrowding [153]. Other researchers have discussed strategies including the use of reserve physicians and nurses [101] and deferring care of low-acuity patients [105,112], either of which could be initiated given a few hours of advance warning prior to overcrowding.

In summary, the findings demonstrate the feasibility of implementing four measures for real-time monitoring of ED crowding. Occupancy level showed discriminatory power similar to or greater than the four other measures for measuring current ED crowding. In terms of timely forecasting, none of the measures showed a clear advantage over occupancy level. These findings suggest new directions for the measurement and management of ED overcrowding.

CHAPTER IV

DISCRETE EVENT SIMULATION

Introduction

Background

The Institute of Medicine recently noted that emergency department (ED) crowding represents an obstacle to the safe and timely delivery of health care [4,43]. Prior research has linked ED crowding with adverse patient outcomes [79-82,89], impaired access to care [64,85-88,94-95, 99], and decreased profitability [97-98,154].

A substantial body of literature has focused on techniques for measuring the phenomenon of ED crowding, with the intent of allowing care providers, administrators, and policy makers to better manage the problem [24-28]. At least two major challenges are associated with measuring ED crowding: First, the lack of a standard crowding definition makes it challenging for unified progress to be made, as different interpretations exist for what the term "crowding" should imply. A recent editorial emphasized the need for measuring ED patient flow, rather than measuring crowding itself [155].

Second, proposed measures of ED crowding have tended to focus on the present crowding state, and reports of forecasting the future crowding state have been relatively recent [30,143,156-158]. Predictions of the near-future status of the ED would arguably have substantial value, because they could trigger early interventions designed to lessen the burden of crowding situations before they arise [101,105,112,120,153]. A focus on forecasting the future, in addition to monitoring the present, may represent the difference between being reactive and being proactive in managing ED crowding.

Importance

Both of the above research gaps may be addressed using a novel application of computer simulation in the ED. We attempt to demonstrate that, with a sufficiently detailed simulation of

ED patient flow, near-future forecasts of almost any crowding measurement of interest may be obtained from a single model. The feasibility of developing an ED simulation model has already been well established [33-34,36,159-164]. Previous studies have focused on using simulation to evaluate the impact of hypothetical changes in ED operations. However, to the best of our knowledge, no previous studies have explored the ability of an ED simulation to serve as a generalized, real-time forecasting model.

Goals of this Investigation

The first goal of this study was to develop a computer simulation for the specific purpose of real-time forecasting of ED operating conditions. The second goal was to validate the ability of the simulation to forecast several different measures of ED crowding.

Methods

Theoretical Model of the Problem

Our study was based on the following premise: With a simulation model that expresses ED crowding in terms of individual patients and their characteristics, perhaps we could forecast any outcome measure of interest. The conceptual process of obtaining forecasts from an ED simulation is outlined in figure 7. The model would consist of a set of theoretical distributions governing patient flow with parameters calculated from historical patient data. The model would be initialized with a detailed list of patients currently in the ED at the observation time of interest, such that the state of the "virtual ED" would mirror the state of the actual ED. The model would then simulate patient flow for several "virtual hours" into the future. Upon halting, the simulation would provide a detailed list of ED patients projected to be present, several hours in the future. Because the output would contain patient-level data, rather than summary variables, theoretically any outcome measure of interest could be calculated to obtain a crowding forecast.

The development of the "ForecastED" model was theoretical, guided by evidence from the literature. An input-throughput-output framework of ED operations was used as the prototype

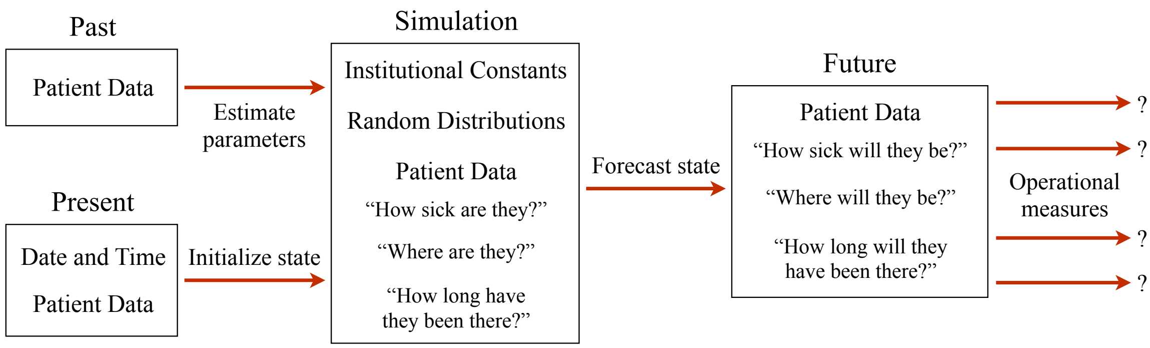

Figure 7. Conceptual process of using a simulation model to forecast crowding. The model would take past and present patient-level data as input and would give future patient-level data as output. Any outcome measure of interest could theoretically be calculated using this information to obtain a forecast.

[22]. Three constraints were placed on the design: The model should 1) reflect care processes that substantially contribute to ED crowding, to facilitate forecasting power; 2) minimize input data requirements, to facilitate generalizability between institutions; and 3) execute quickly, to facilitate real-time forecasting. An interdisciplinary team, consisting of experts in patient care, operations research, medical informatics, and biostatistics, developed the model. The development proceeded iteratively until all team members agreed that the constraints were satisfied. The design of the final model is presented in figure 8.

Patient arrivals (figure 8, point A). We assumed that patient arrival rates vary according to the time of day and day of week [165]. We represented patient arrivals using a non-stationary Poisson process [34], where a exponential distribution governed the time between arrivals [32]. The simulation uses a previously reported algorithm to implement the random non-stationary Poisson process over the 168 hours in a week [166].

Decisions to leave without being seen (figure 8, point B). Some patients leave the ED without being seen [64,95], and we assumed this decision would be influenced by the waiting room count [92]. We represented this process using a logistic regression model with the waiting room count as the independent variable and whether the patient left without being seen as the dependent variable. The simulation transforms the log odds to a probability of leaving without be-

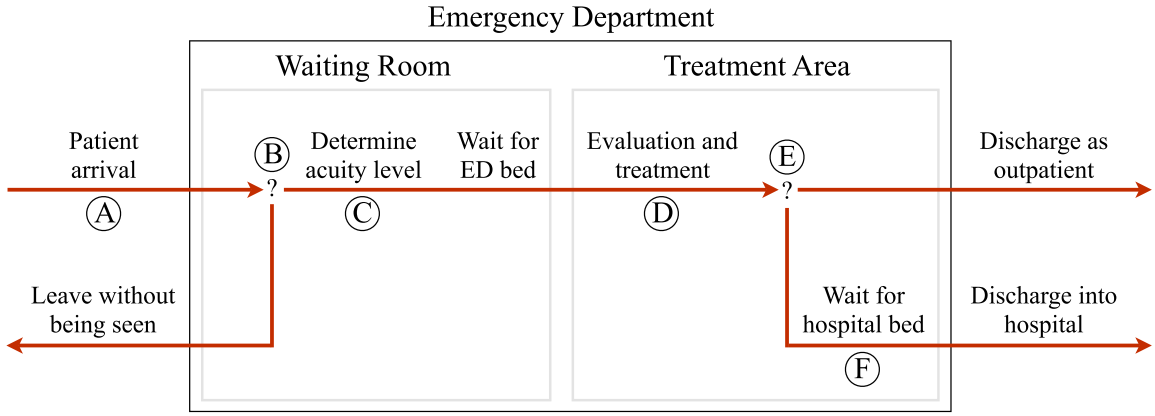

Figure 8. Diagram of patient flow through the ForecastED simulation. Six random processes, marked by circled letters, drive all aspects of patient flow: A) patient arrivals as a non-stationary Poisson process, dependent on the time of the day and day of the week; B) decisions to leave without being seen as a Bernoulli trial, dependent on the waiting room count; C) patient acuity levels as a multinomial distribution; D) duration of evaluation and treatment as a log-normal distribution, dependent on the acuity level; E) hospital admission decisions as a Bernoulli trial, dependent on the acuity level; and F) hospital bed openings as a non-stationary Poisson process, dependent on the time of the day and day of the week.

ing seen for each patient [167], and then uses a random Bernoulli trial to determine whether the patient would leave.

Triage category assignment (figure 8, point C). Patients are commonly triaged using an ordinal ranking scheme [145,168-169]. We represented the chance of belonging to each acuity level using a multinomial distribution [32]. The simulation places the most urgent patients into bed immediately, without regards to bed availability. This provides a mechanism by which, under extreme operating conditions, the licensed capacity may be exceeded out of necessity. The simulation retains all other patients in the waiting room, prioritizing them for beds by the most urgent acuity level and resolving ties according to waiting time. The simulation allows the number of acuity levels and licensed beds to vary between institutions.

Evaluation and treatment (figure 8, point D). We assumed that sicker patients generally require more extensive ED care. The log-normal, gamma, and Weibull distributions all take similar shapes and commonly govern service time patterns [32]. The simulation uses a separate log-normal distribution within each acuity level to represent the duration of evaluation and treatment after bed placement for each patient.

Decision for hospital admission (figure 8, point E). We assumed that sicker patients would be more frequently admitted to the hospital. Upon completion of the evaluation and treatment for each patient, the simulation uses a random Bernoulli trial to determine whether the patient should be admitted. The simulation uses a separate admission probability for each acuity level. The simulation immediately discharges outpatients, while it retains admitted patients in the ED pending hospital bed availability.

Hospital bed openings (figure 8, point F). Boarding of admitted patients in the ED has been suggested to be a major contributor to ED crowding [16,62]. We assumed that some hospital processes, such as operating room schedules, affect inpatient bed availability according to daily and weekly patterns. The simulation represents the process of hospital bed openings using a non-stationary Poisson process, analogous to the one used to represent patient arrivals [32,166]. The simulation prioritizes admitted patients for hospital beds according to boarding time.

We implemented the ForecastED simulation using the standard C programming language. The simulation generates all random numbers using the Mersenne Twister algorithm, which has been statistically validated for the purpose of simulation [170].

Study Design

We validated the ForecastED simulation model using historical data from consecutive patient encounters during a 400-day period (12/1/2005 – 1/5/2007). The study did not involve any direct patient contact, and the local Institutional Review Board approved it by expedited review.

Setting

The validation took place in the adult ED of a tertiary-care, urban, academic medical center with a Level 1 trauma service. The adult ED provides care for more than 50,000 patients annually. It contains 41 licensed, monitored beds, including four trauma beds. Four additional fast-track beds are available for low-acuity patients from 11 AM to 11 PM, and eight dedicated rooms are available for psychiatric patients. Patients are triaged according to the Emergency Severity Index (ESI), an ordinal score ranging from one, for the most urgent patients, to five, for the least urgent patients [145]. Hospital policy allows for the ED to initiate ambulance diversion if any of the following criteria are true, and are not expected to improve within one hour: "1) all critical care beds in the ED are occupied, patients are occupying hallway spaces, and at least 10 patients are waiting; 2) an acuity level exists that places additional patients at risk; or 3) all monitored beds within the ED are full." In practice, ambulance diversion is generally initiated when all licensed beds are occupied and 10 or more patients are in the waiting room.

Selection of Participants

We used data from all patients who received care in the adult ED during the study period, with the following exceptions: Patients with only psychiatric complaints were excluded because they are treated in a separate unit, and crossover between general-purpose and psychiatric beds is rare. Patients who were dead on arrival to the ED, as well as patients who were directly admitted to a critical care unit without being treated in the ED, were excluded because they were not considered substantial contributors to ED crowding.

Data Collection and Processing

The following describes the minimal set of patient-level variables required for the simulation: 1) time of initial registration at the ED, 2) time placed into an ED treatment bed, 3) time of hospital bed request if applicable, 4) time of discharge from the ED facility, 5) triage category assigned to the patient, and 6) whether the patient left without being seen. We obtained these patient data from the ED information systems, which collect the data during normal ED operations using a real-time patient tracking application. Ambulance diversion log files were obtained from the hospital's aeromedical service.

We validated the simulation's forecasting ability at consecutive 10-minute observations during 2006 (n = 52,560) using the conceptual method described above and outlined in figure 7.

At every observation, the parameters of each random distribution required by the simulation were re-fit by maximum likelihood estimation using the preceding four weeks of historical patient data. This sliding-window validation technique, illustrated in figure 9, ensured that the data used for fitting were separate from the data used for validation at all times. This also ensured that the parameters remained up-to-date throughout the year to reflect seasonal variations. At every observation, we used the mean of 1000 simulation replications to obtain 2-hour, 4-hour, 6-hour, and 8-hour forecasts of several crowding measures [32].

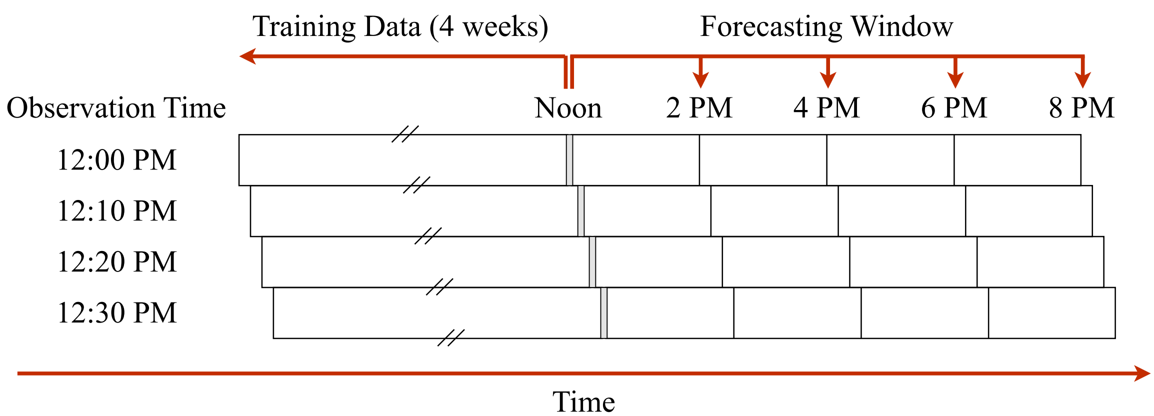

Figure 9. Application of the sliding-window validation technique. At consecutive 10-minute observations, the distribution parameters were re-estimated using four weeks of historical patient data. The simulation was used to forecast operating conditions at varying time points in the future. This technique ensured the data used for fitting and validation never overlapped.

Outcome Measures

We forecast the following measures of ED crowding at every observation: 1) waiting count, defined as the number of patients in the waiting room; 2) waiting time, defined as the average time since presentation among patients in the waiting room; 3) occupancy level, defined as the total number of patients in ED beds divided by the number of licensed treatment beds (this value may exceed 100% when patients are treated in non-licensed areas such as hallway beds or chairs); 4) length of stay, defined as the average time since presentation among all patients in ED beds; 5) boarding count, defined as the number of patients awaiting hospital admission; 6) boarding time, defined at the average time since hospital bed request among patients awaiting hospital admission; and 7) probability of ambulance diversion, defined as a close approximation of the local diversion policy using the probability of having 10 or more patients in the waiting room and an occupancy level of at least 100%. The reference standard for validating each forecast outcome measure was the actual outcome measure at the respective point in the future.

Primary Data Analysis

We checked the assumptions underlying the simulation's random processes by comparing the observed and theoretical distributions for all patients receiving care during 2006.

We used the Pearson's r coefficient of correlation to measure the reliability of the simulation forecasts for each continuous outcome measure in comparison with the reference standard. The Pearson's r measures the strength of linear association and, when squared, summarizes the fraction of explained variation in the outcome. The Pearson's r was calculated with 95% confidence intervals (CI) using 250 iterations of the ordinary bootstrap method [171].

Substantial autocorrelation likely exists in the time series of each continuous outcome measure. Thus, the present state of the ED may be considered a naïve forecast of the future state of the ED. To provide a control measure for judging the reliability of the simulation forecasts, we measured the autocorrelation coefficient for each reference standard time series at lags of 2, 4, 6, and 8 hours. The autocorrelation coefficient is equivalent to the Pearson's r between a series and a time-delayed version of itself. The autocorrelation coefficients were calculated with 95% CI using 250 iterations of the ordinary bootstrap method [171].

Correlation coefficients alone do not imply good calibration of the simulation forecasts [172]. To detect any presence of bias, we calculated the mean and standard deviation of the residual difference between each continuous outcome measure and the reference standard. A residual mean that differs from zero, in proportion to the standard deviation, indicates the presence of a systematic bias in the forecasts.

We calculated the discriminatory power of the simulation forecasts for ambulance diversion using the area under the receiver operating characteristic curve (AUC). The AUC summarizes overall discriminatory power for the outcome, where a value of 1.0 represents perfect discrimination and a value of 0.5 represents no discrimination [146]. The AUC was calculated with 95% CI using 250 iterations of the ordinary bootstrap method [171].

We measured the total time required to execute the simulation during the experiment, since computational time would be a consideration for the real-time application of the ForecastED system. All statistical analyses were conducted using the R software package (version 2.3.1, http://www.r-project.org).

Results

A total of 57,995 patients visited the adult ED during the study period, of which 4,776 patients were excluded (8.2%). A total of 188 ambulance diversion episodes occurred during the 2006 calendar year, each lasting an average of 10.7 hours.

The distributions of observed and theoretical random distributions governing the ForecastED model are shown in figure 10. The theoretical distributions closely matched the observed distributions. The average rate of patient arrivals ranged from a minimum of 1.6 per hour on Thursdays from 4 AM to 5 AM, to a maximum of 10.3 per hour on Mondays from 11 AM to 12 PM. The probability of each patient leaving without being seen increased smoothly from 0.6% with no patients in the waiting room to 4.8% with 15 patients in the waiting room. The fraction of patients assigned to each triage category for acuity levels 1 through 5, respectively, was 0.7%, 37.8%, 44.2%, 15.8%, and 1.4%. The median duration of treatment for acuity levels 1 through 5, respectively, was 4.0 hours, 4.6 hours, 3.1 hours, 1.7 hours, and 1.2 hours. The probability of hospital admission for acuity levels 1 through 5, respectively, was 73.1%, 45.3%, 17.1%, 2.7%, and 1.0%. The average rate of hospital bed openings ranged from a minimum of 0.1 per hour on Thursdays from 7 AM to 8 AM, to a maximum of 3.3 per hour on Fridays from 9 PM to 10 PM.

The reliability of the simulation forecast for each continuous outcome measure is presented in table 8. The simulation forecasts showed equal or greater reliability for predicting future operating conditions than the autocorrelation inherent in each reference standard across all

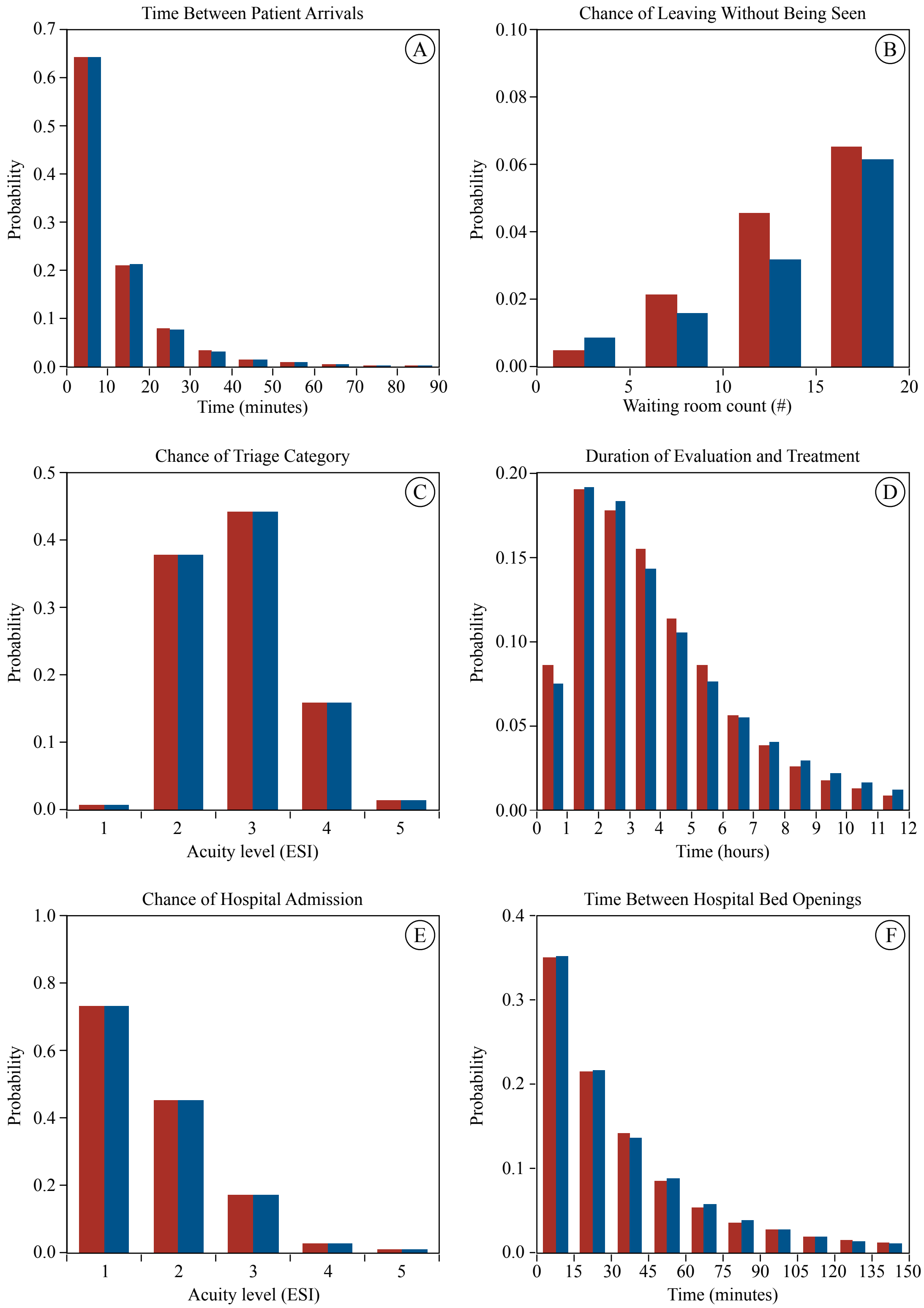

Figure 10. Observed and theoretical distributions of the random processes in ForecastED: A) time between patient arrivals, B) probability of leaving without being seen as a function of the waiting room count, C) probability of being assigned to each triage category, D) duration of ED evaluation and treatment, E) probability of hospital admission as a function of the acuity level, and F) time between hospital bed openings. The observed distributions are shown in red, and the theoretical distributions are shown in blue.

forecasting lengths. The reliability decreased as the length of the forecasting window increased. For example, the simulation forecasts of the waiting room count had correlation coefficients of 0.79, 0.70, 0.62, and 0.56, respectively, with the actual waiting room count at 2, 4, 6, and 8 hours in the future. Moreover, the difference in reliability between the simulation forecasts and the inherent autocorrelation increased as the forecasting window increased. For example, the simulation forecasts of occupancy level had correlation coefficients of 0.91, 0.85, 0.81, and 0.78, respectively, with the actual occupancy level at 2, 4, 6, and 8 hours in the future. By contrast, the autocorrelation of the occupancy level was 0.84, 0.61, 0.35, and 0.15 at lags of 2, 4, 6, and 8 hours.

Table 8. Reliability of the simulation versus autocorrelation in forecasting operational data

	2 hours ahead	4 hours ahead	6 hours ahead	8 hours ahead
Waiting count				
Simulation	0.79 (0.79, 0.80)	0.70 (0.69, 0.70)	0.62 (0.61, 0.62)	0.56 (0.55, 0.57)
Autocorrelation	0.76 (0.75, 0.76)	0.52 (0.51, 0.52)	0.26 (0.25, 0.27)	0.04 (0.03, 0.05)
Waiting time				
Simulation	0.74 (0.73, 0.75)	0.66 (0.65, 0.67)	0.57 (0.56, 0.58)	0.49 (0.48, 0.50)
Autocorrelation	0.64 (0.63, 0.65)	0.44 (0.43, 0.45)	0.28 (0.27, 0.29)	0.15 (0.14, 0.16)
Occupancy level				
Simulation	0.91 (0.91, 0.91)	0.85 (0.85, 0.85)	0.81 (0.81, 0.81)	0.78 (0.77, 0.78)
Autocorrelation	0.84 (0.83, 0.84)	0.61 (0.60, 0.61)	0.35 (0.35, 0.36)	0.15 (0.13, 0.15)
Length of stay				
Simulation	0.96 (0.95, 0.96)	0.92 (0.92, 0.92)	0.89 (0.89, 0.89)	0.86 (0.86, 0.86)
Autocorrelation	0.94 (0.94, 0.94)	0.85 (0.85, 0.86)	0.76 (0.76, 0.77)	0.68 (0.67, 0.68)
Boarding count				
Simulation	0.94 (0.94, 0.94)	0.89 (0.89, 0.89)	0.84 (0.83, 0.84)	0.79 (0.79, 0.80)
Autocorrelation	0.94 (0.93, 0.94)	0.88 (0.88, 0.88)	0.82 (0.82, 0.83)	0.77 (0.76, 0.77)
Boarding time				
Simulation	0.88 (0.88, 0.88)	0.84 (0.84, 0.85)	0.82 (0.81, 0.82)	0.80 (0.80, 0.80)
Autocorrelation	0.87 (0.87, 0.88)	0.78 (0.77, 0.78)	0.68 (0.67, 0.68)	0.59 (0.58, 0.59)

The Pearson’s r coefficient of correlation is presented with lower and upper bounds of the 95% confidence interval in parentheses.

The calibration of the simulation forecast for each continuous outcome measure is presented in table 9. The model showed good calibration, as defined by the residual mean having small magnitude in proportion to the standard deviation, for all outcome measures except the boarding time. The model consistently underestimated the average hours of boarding time at 2, 4, 6, and 8 hours in the future, respectively, by -6.1 ± 2.5, -6.8 ± 2.9, -7.1 ± 3.2, and -7.3 ± 3.4, indicating a systematic bias for this outcome measure.

Table 9. Calibration of the simulation in forecasting operational data

	2 hours ahead	4 hours ahead	6 hours ahead	8 hours ahead
Waiting count (# of patients)	-0.6 ± 3.6	-0.1 ± 4.7	0.3 ± 5.3	0.5 ± 5.7
Waiting time (hours)	-0.1 ± 0.5	0.0 ± 0.7	0.2 ± 0.9	0.3 ± 1.0
Occupancy level (% of beds)	0.9 ± 9.0	1.0 ± 11.3	1.3 ± 12.6	1.6 ± 13.5
Length of stay (hours)	-0.8 ± 1.0	-0.9 ± 1.3	-1.0 ± 1.5	-0.9 ± 1.7
Boarding count (# of patients)	-0.4 ± 2.4	-0.7 ± 3.1	-0.9 ± 3.7	-1.1 ± 4.2
Boarding time (hours)	-6.1 ± 2.5	-6.8 ± 2.9	-7.1 ± 3.2	-7.3 ± 3.4

The forecasting residuals are summarized with the mean ± standard deviation.

The receiver operating characteristic curves for discriminating ambulance diversion in the future are presented in figure 11. The AUC at 2, 4, 6, and 8 hours in the future, respectively, was 0.88 (95% CI: 0.88, 0.88), 0.88 (95% CI: 0.88, 0.89), 0.88 (95% CI: 0.88, 0.88), and 0.86 (95% CI: 0.86, 0.87), indicating high discriminatory power.

The entire validation required 28,989 seconds of execution time using a 1.83 GHz Intel Core Duo processor, indicating each group of 1,000 simulation replications took 0.55 seconds to execute. In other terms, the simulation ran approximately 130 million times faster than real time.

Limitations

One potential limitation of this study is the narrow purpose for which the ForecastED simulation was intended. We developed and validated it for the sole purpose of forecasting near-

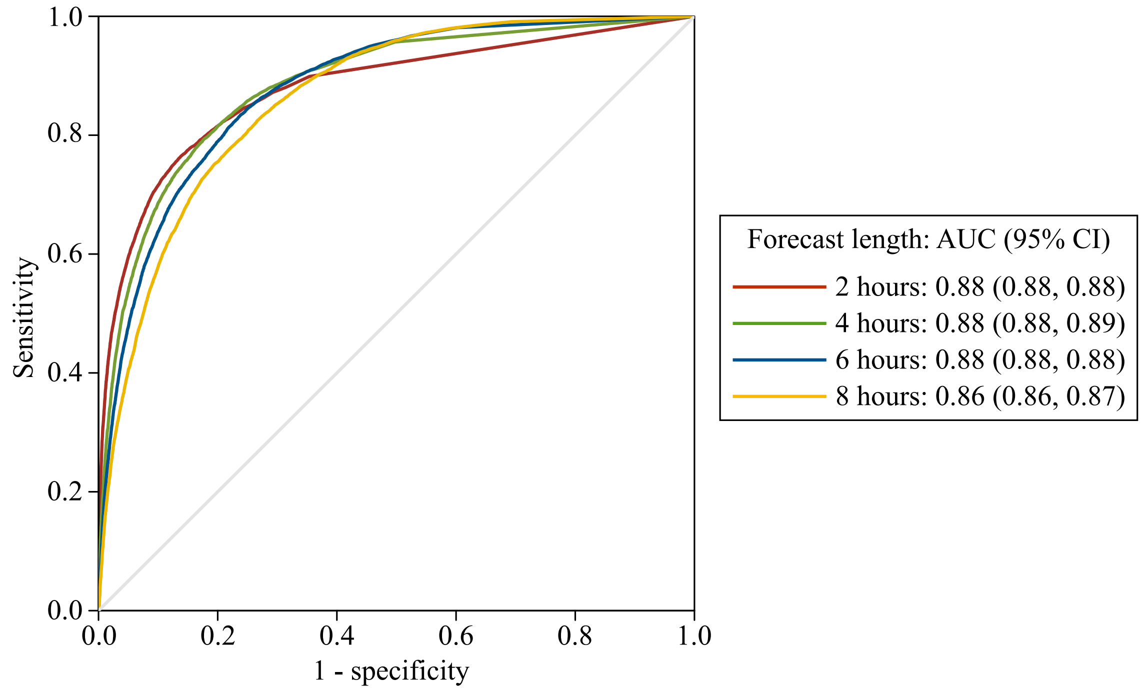

Figure 11. Receiver operating characteristic curves of ambulance diversion forecasts. The AUC with 95% CI is shown in parentheses, describing the discriminatory power at varying time points in the future.

future operational measures in the ED. We intentionally kept the purpose narrow, because an effort to create an all-purpose simulation of ED patient flow might have compromised one or more of our design goals. Its use for other common applications of simulation, such as evaluating long-term effects of proposed organizational changes, may not be warranted.

A number of objections may be made regarding aspects of ED patient flow that the ForecastED simulation did not model. We assumed the times required for triaging patients and for cleaning treatment areas to be negligible. We did not include a mechanism for patient death in the ED. We excluded institution-specific care processes, including fast-track beds and designated psychiatric areas. Different aspects of ED evaluation and treatment, such as radiological exams and pending consults, were grouped into a single process representing their total duration. We counter these objections by noting that "all models are wrong, but some are useful" [173]. The validation results demonstrate that, despite its relatively simple design, our model provides accurate forecasts.

We conducted a single-center validation, so the findings do not allow for comment on how well the ForecastED simulation would generalize to other institutions. However, the simulation design includes only processes that would likely apply to diverse EDs, including large academic centers and small community-based centers. We emphasized the use of patient-level data that are increasingly becoming available using ED information systems. Also, the probability distributions that govern the simulation may be continuously re-estimated using site-specific historical patient data, adjusting for differences in volume or demographics between institutions.

Our study design allowed the model accuracy to be measured, but the question of how timely interventions based on the forecasts would affect patient care remains unanswered. Knowledge of the future alone cannot solve the crowding problem; action based on this knowledge is required. This is the intended application of the simulation, and further research will be necessary to determine whether the ForecastED simulation can alleviate the negative effects of crowding.

Discussion

We have designed and implemented ForecastED, a discrete event simulation that uses patient flow to predict near-future ED operational measures. The findings indicate that the distributions used to represent the model's random processes closely fit the observed data. The simulation forecasts correlated well with the actual operational measures at 2, 4, 6, and 8 hours in the future. This correlation equalled or exceeded the inherent autocorrelation of the data across all outcome measures and forecast lengths. The simulation forecasts showed good calibration for all of the outcome measures except the boarding time, which was systematically biased. The findings also demonstrate that the simulation may be used to forecast the probability of ambulance diversion status, and these forecasts showed high discriminatory power up to 8 hours into the future.

The forecasts of boarding time were systematically biased, perhaps with the following explanation: When hospital bed openings occur, the simulation allocates each bed to the patient who has been boarding the longest. In an actual ED, the hospital bed allocation may occur differently, considering specific hospital services to which patients might be admitted. Individual boarding times are likely to be skewed to the right, so the simulation repeatedly removes outliers that strongly influence the average. The bias may be reduced in two ways, without requiring changes to the simulation design: 1) Calibrate the boarding time by adding a constant to each forecast, or 2) use the median to summarize individual boarding times instead of the mean, compensating for the skewed distribution.

While many outcome measures beyond those used for validation are possible, the selected measures of ED crowding represent two input, two throughput, and two output measures corresponding to a conceptual model of crowding [22]. The simulation may also be applied to forecast the probability of overcrowding as a binary state. It is agnostic to what specific definition of overcrowding is applied; the only restriction is that overcrowding must be defined in terms of objective, patient-level data. This differs from a standard regression model, where the model would be dependent on a specific definition of overcrowding. The flexible capability of the ForecastED system may represent an inherent strength of the simulation approach.

Because the ForecastED simulation describes the state of the ED in terms of the patients present, any crowding measure that can be expressed by patient-level data may theoretically be forecast using the model. We calculated that the level of detail reflected in the ForecastED simulation should be sufficient to forecast near-future values of many of the measures described by a consensus of experts [23], as well as the Emergency Department Work Index (EDWIN), the National Emergency Department Overcrowding Scale (NEDOCS), the Work Score, the Emergency Department Crowding Scale (EDCS), and the Real-Time Emergency Analysis of Demand Indicators (READI) scores [24-28].

The simplicity of the ForecastED simulation provides several practical advantages: First, the simulation contains no ad hoc parameters. All of the distributions that govern the simulation processes may be estimated directly from patient data at any given institution. Second, only six per-patient variables are required for the simulation. Many EDs may already have the necessary data for the real-time deployment of our system. Third, we implemented the simulation using the platform-independent C programming language, which may benefit execution speed and portability between institutions. The ForecastED system is not intended as an offline tool for change management; rather, it is intended as a real-time forecasting tool to reflect the dynamic state of ED operations.

In summary, we have developed and validated the ForecastED simulation, which may be used to forecast the values of various ED crowding measurements at points in the near future. An old management adage notes that "you cannot manage what you cannot measure," and the approach manifest by the ForecastED simulation may represent a step towards empowering EDs to proactively manage the problem of crowding.

CHAPTER V

PROSPECTIVE EVALUATION

Introduction

The Emergency Medical Treatment and Active Labor Act (EMTALA) [5], passed in 1986 by Congress as part of the Consolidated Omnibus Budget Reconciliation Act, mandates that all patients presenting to an emergency department (ED) must be screened and stabilized, regardless of medical condition or ability to pay. Emergency medical services are the only form of health care in the United States legally guaranteed to be accessible, providing an important safety net [2,174]. A seemingly clairvoyant article published in 1958 recommended that the number of EDs should increase in preparation for future demand [175]. Unfortunately, between 1990 and 2005 the annual number of ED visits increased from 87 million to 115 million, while the number of EDs decreased from 5172 to 4611 [3]. Due to the growing problem of crowding, the Institute of Medicine found in 2006 that American EDs are “at the breaking point” [4]. Prior research has shown that the consequences of ED crowding, which include delayed treatment [88-89], patient elopement [94,96], prolonged transport [84,86], increased mortality [80,82], and financial losses [97,176], are numerous and affect the entire health care system.

The ability to forecast near-future ED crowding should enable new strategies of coping with the problem. For instance, a tool that accurately describes operating conditions several hours into the future might allow for 1) just-in-time dynamic resource mobilization or 2) coordination of primary care, hospital, and ED processes. Several measures of ED crowding have been proposed, including the Emergency Department Work Index (EDWIN) [24], the Real-time Emergency Analysis of Demand Indicators (READI) [25], the National Emergency Department Overcrowding Scale (NEDOCS) [26], the Emergency Department Crowding Scale (EDCS) [27], and the Work Score [28]. These measures can accurately reflect present ED crowding, although they do not attempt to forecast future ED crowding [144,158].

Reports in the literature have described efforts to forecast ED crowding using techniques such as time series regression [29], deterministic modeling by differential equations [30], and discrete event simulation [177]. In the latter, we described the development and retrospective validation of ForecastED, a simulation-based tool to forecast ED crowding in the near future [177]. We based the decision to use discrete event simulation on the following rationale: Crowding is a complex phenomenon that can be summarized by numerous different measures [22-23], such as the number of waiting patients, boarding patients, or occupied beds. Most forecasting techniques require the investigator to select a dependent variable prior to model development. By contrast, a discrete event simulation can output a detailed list of patients projected to be in the ED in the future, and from this information the forecasts of many different outcome measures can be derived.

To our knowledge, no previous report has demonstrated the application of an instrument to forecast ED crowding in real time. This research gap must be addressed before a forecasting system can achieve practical value. The first objective of this study was to demonstrate the feasibility of integrating the ForecastED tool with existing ED information systems. The second objective was to quantify its ability to predict near-future values of several crowding measures in a live, operational setting.

Methods

Design

We prospectively validated the ForecastED tool during a three-month period (5/1/2007 – 8/1/2007). The study did not involve any direct patient contact, and the local Institutional Review Board approved the study by expedited review.

Setting

We conducted the study in the adult ED of a tertiary-care, urban, academic Level 1 trauma center. The adult ED cares for more than 50,000 patients annually. It contains 41 licensed, monitored beds, four of which are designated for trauma patients. In addition, four fast-track beds are available for patients with minor complaints from 11 AM to 11 PM, and eight dedicated rooms are available for patients with psychiatric complaints. Patients are triaged by the Emergency Severity Index (ESI), an ordinal score ranging from one, for the most urgent patients, to five, for the least urgent patients [145]. Institutional policy allows for ambulance diversion if any of the following criteria are true, and are not expected to improve within one hour: “1) all critical care beds in the ED are occupied, patients are occupying hallway spaces, and at least 10 patients are waiting; 2) an acuity level exists that places additional patients at risk; or 3) all monitored beds within the ED are full.” In practice, the administrator on duty initiates ambulance diversion when all licensed beds are occupied and at least 10 patients are in the waiting room. The ED staff were blinded to the study to avoid one potential source of bias.

Participants

We included data from all patients who received care in the adult ED during the validation period, with the following exceptions: We excluded visits involving purely psychiatric complaints because they are treated in a separate unit, and little crossover occurs between general-purpose and psychiatric beds. We excluded visits by patients who were dead on arrival to the ED, as well as visits by patients who were admitted directly to a hospital unit without receiving care in the ED, because these patients generally consume little ED resources at our institution. Because the study was conducted in real time, information that identified a patient for exclusion was not always available immediately. Such patients remained in the study until the time that information became available to exclude them.

Data

To enable real-time forecasting of crowding, we developed a computer program using the Python programming language (version 2.3.5, http://www.python.org). This integration software linked the core ForecastED tool with existing information systems, automating the process of obtaining forecasts. The functions of this program were to obtain de-identified patient data from local ED information systems, to provide these data to ForecastED as input, to record the subsequent forecasts using a research database, and to display the output using the graphical web interface shown in figure 12. Six patient-level variables were obtained from ED information systems when needed [177]: 1) time of initial registration at the ED, 2) time placed into an ED treatment bed, 3) time of hospital bed request if applicable, 4) time of discharge from the ED facility, 5) triage category assigned to the patient, and 6) whether the patient left without being seen.

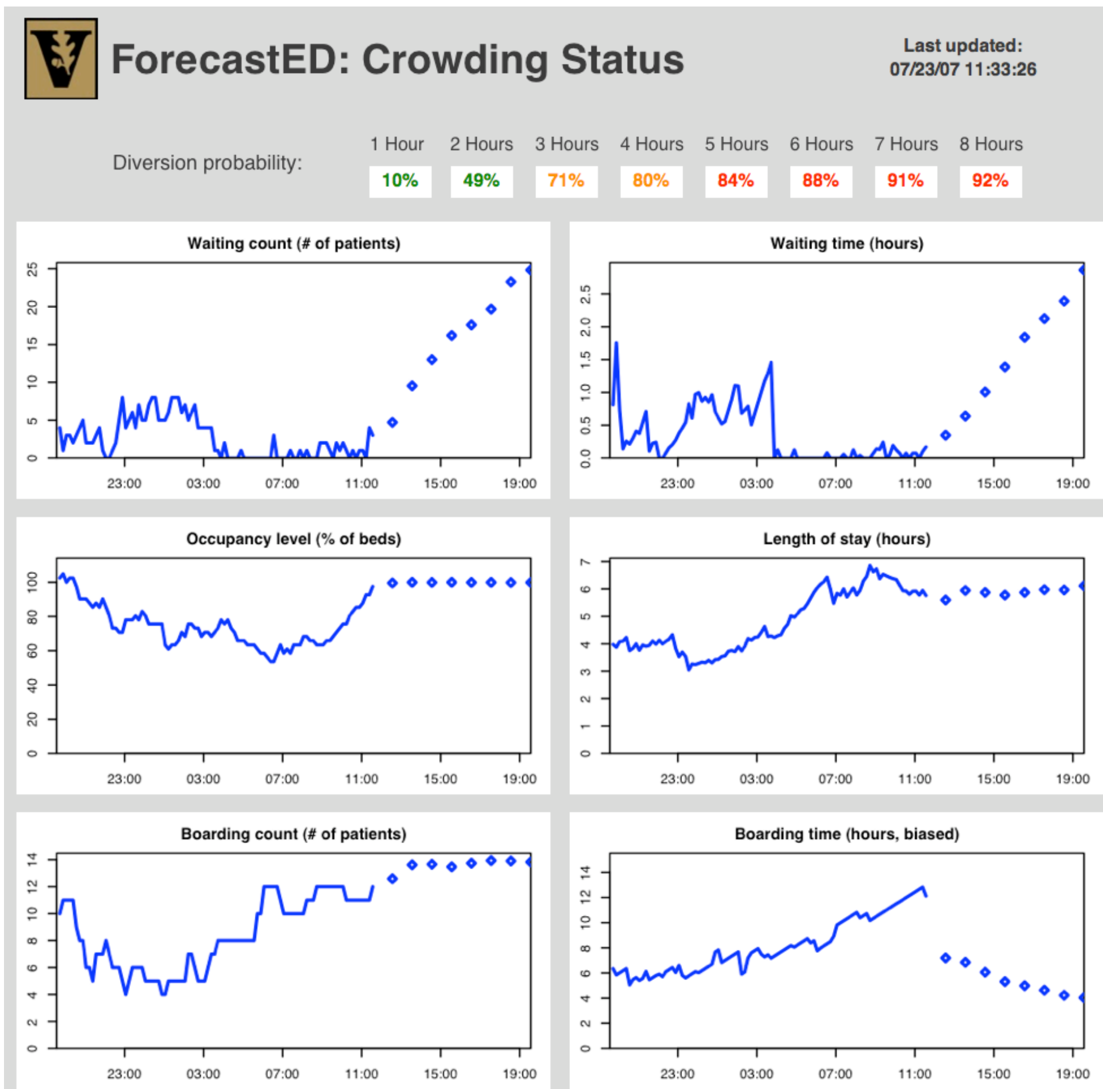

Figure 12. Graphical web interface of the ForecastED output. As indicated in the upper right, this screenshot was captured on a Monday (July 23, 2007) shortly before noon, which is commonly a time of rapid patient inflow. Across the top, the forecasts of ambulance diversion probability at 1 hour, 2 hours, and up to 8 hours into the future are displayed. Most of the screenshot is occupied by time series plots for six crowding measures, where the solid line indicates the actual values observed during the previous 16 hours, and the diamonds indicate the forecast values for the next 8 hours.

Forecasting

The technical details and assumptions of the ForecastED tool have been described in previous work [177]. Briefly, the tool is a discrete event simulation that consists of several random number distributions that are structured to represent the flow of individual patients through the ED [32]. It may be considered a computerized model of a virtual ED – patients have varying degrees of sickness, form queues in the waiting room, receive care in licensed beds – with the key difference being that time flows much faster in the virtual ED than in the actual ED. This property allowed us to initialize the virtual ED based on the known state of the actual ED, instantly move through several hours of simulated time, and obtain crowding measurements at a desired point in the future.

The integration software performed two tasks at regular intervals: 1) Every day at midnight, the program used the most recent four weeks of historical patient data to estimate the parameters of each random number distribution needed for the simulation. This was intended to keep the simulated processes up-to-date despite long-term fluctuations that might occur in patient demand or local workflow. 2) At every 10-minute interval, the program identified the set of patients presently in the ED and initialized the ForecastED tool accordingly. It used the mean of 1000 simulation replications to obtain forecasts of several crowding measures at each hourly interval up to 8 hours into the future [178].

Outcomes

We obtained forecasts of seven distinct crowding measures at 10-minute intervals: 1) waiting count, defined as the number of patients in the waiting room; 2) waiting time, defined as the average time since presentation among patients in the waiting room; 3) occupancy level, defined as the total number of patients in ED beds divided by the number of licensed treatment beds (this value may exceed 100% when patients are treated in non-licensed areas such as hallway beds or chairs); 4) length of stay, defined as the average time since presentation among all patients in ED beds; 5) boarding count, defined as the number of patients awaiting hospital admission; 6) boarding time, defined as the average time since hospital bed request among patients awaiting hospital admission; and 7) probability of ambulance diversion, defined as a close approximation of the local diversion policy using the probability of having 10 or more patients in the waiting room and an occupancy level of at least 100%. These outcome measures were identical to those used in the preliminary, retrospective validation of ForecastED [177].

We used the actual outcome measure, from the corresponding point in the future, as the reference standard for validating each forecast. At the time when each forecast was recorded, the value of the reference standard was not yet known. After the validation period ended, we obtained actual values of the six continuous outcome measures from information systems. The local aeromedical service, which maintains official records of diversion status independently of the ED, provided ambulance diversion log files.

Analysis

We validated the simulation forecasts of each outcome measure 2, 4, 6, and 8 hours into the future. We used the coefficient of determination (R^2) to measure the reliability of the simulation forecasts for each continuous outcome measure with respect to the reference standard. This statistic describes the percentage of variation in the future outcome measures explained by the simulation forecasts. We calculated the R^2 with 95% confidence intervals (CI) using 250 iterations of the ordinary bootstrap method [171].

The values of R^2 would not be affected by the calibration of the simulation forecasts [172]; furthermore, because ForecastED was not fitted to predict any specific dependent variable in the least-square sense, it would have been erroneous to assume the residuals were centered around zero. We investigated the possible bias by calculating the mean and standard deviation of the residual forecasting error for each continuous outcome measure. A residual mean differing from zero, with respect to the standard deviation, would reveal the presence of a systematic bias in the forecasts.

We calculated the area under the receiver operating characteristic curve (AUC) to assess the discriminatory power in forecasting ambulance diversion status. This statistic summarizes overall discriminatory power for a binary outcome, where a value of 1.0 denotes perfect discrimination and a value of 0.5 denotes no discrimination [146]. We calculated the AUC with 95% CI using 250 iterations of the ordinary bootstrap method [171]. All statistical analyses were conducted using R (version 2.3.1, http://www.r-project.org).

Results

During the study period, a total of 13,239 10-minute intervals were observed out of a possible 13,248 (99.9%). Brief network downtimes accounted for the missed observations. A total of 14,448 visits by 11,539 unique patients occurred in the adult ED during the study period, of which 1,348 visits were excluded (9.3% total, 1.0% psychiatric, 0.0% dead on arrival, 8.3% immediately admitted to the hospital). Females represented 54.9% of the total patients, and the median age was 39 years. A total of 73.8% of the patients arrived by car, 17.1% by ambulance, 2.2% by helicopter, and 6.9% by other or unknown means. Hospital admissions resulted from 22.7% of the ED visits. A total of 77 ambulance diversion episodes, each lasting an average of 5.4 hours, occurred during the study period (18.8% of the total time).

The reliability of the simulation forecast for each continuous outcome measure is presented in table 10. The forecasts explained more than 50% of the variation in the occupancy level, length of stay, boarding count, and boarding time up to 8 hours into the future. The percentage of future variation explained decreased as the length of the forecasting window increased. For example, the simulation forecasts of the occupancy level had R^2 values of 0.76, 0.67, 0.61, and 0.57, respectively, in predicting the actual occupancy level 2, 4, 6, and 8 hours into the future.

The calibration of the simulation forecast for each continuous outcome measure is presented in table 11. The residual mean had small magnitude, relative to the standard deviation, for every outcome measure except the boarding time, suggesting that the forecasts were unbiased for most measures of crowding studied. The model consistently underestimated the boarding time 2,

Table 10. Reliability of the simulation in forecasting operational data

	2 hours ahead	4 hours ahead	6 hours ahead	8 hours ahead
Waiting count (R^2)	0.53 (0.52, 0.55)	0.40 (0.39, 0.42)	0.32 (0.31, 0.34)	0.27 (0.26, 0.29)
Waiting time (R^2)	0.32 (0.29, 0.35)	0.22 (0.20, 0.24)	0.15 (0.13, 0.17)	0.11 (0.10, 0.12)
Occupancy level (R^2)	0.76 (0.75, 0.76)	0.67 (0.66, 0.68)	0.61 (0.60, 0.62)	0.57 (0.55, 0.58)
Length of stay (R^2)	0.87 (0.87, 0.88)	0.80 (0.80, 0.81)	0.74 (0.73, 0.75)	0.69 (0.68, 0.70)
Boarding count (R^2)	0.84 (0.84, 0.85)	0.74 (0.73, 0.75)	0.67 (0.66, 0.68)	0.61 (0.59, 0.62)
Boarding time (R^2)	0.70 (0.69, 0.71)	0.61 (0.60, 0.62)	0.56 (0.55, 0.57)	0.53 (0.51, 0.54)

The coefficient of determination is presented with lower and upper bounds of the 95% confidence interval in parentheses.

4, 6, and 8 hours into the future, respectively, by -6.6 ± 2.7, -7.3 ± 3.1, -7.7 ± 3.3, and -7.8 ± 3.5, demonstrating a systematic bias for this outcome measure.

The receiver operating characteristic curves for discriminating future ambulance diversion status are presented in figure 13. The AUC at 2, 4, 6, and 8 hours into the future, respectively, was 0.93 (95% CI: 0.93, 0.94), 0.90 (95% CI: 0.90, 0.91), 0.88 (95% CI: 0.87, 0.88), and 0.85 (95% CI: 0.84, 0.86), suggesting good discrimination. To illustrate the response of the ForecastED tool to periods of ED crowding, figure 14 shows a time series plot of the 6-hour forecast probability of ambulance diversion, superimposed on episodes of ambulance diversion.

Table 11. Calibration of the simulation in forecasting operational data

	2 hours ahead	4 hours ahead	6 hours ahead	8 hours ahead
Waiting count (# of patients)	0.0 ± 4.5	0.9 ± 5.8	1.6 ± 6.5	2.2 ± 7.0
Waiting time (hours)	-0.1 ± 0.6	0.1 ± 0.9	0.3 ± 1.1	0.5 ± 1.3
Occupancy level (% of beds)	2.4 ± 9.6	2.5 ± 11.2	2.9 ± 12.1	3.3 ± 12.9
Length of stay (hours)	-0.7 ± 1.0	-0.8 ± 1.3	-0.8 ± 1.5	-0.8 ± 1.6
Boarding count (# of patients)	0.3 ± 2.5	0.2 ± 3.1	0.1 ± 3.6	0.1 ± 3.9
Boarding time (hours)	-6.6 ± 2.7	-7.3 ± 3.1	-7.7 ± 3.3	-7.8 ± 3.5

The forecasting residuals are summarized with the mean ± standard deviation.

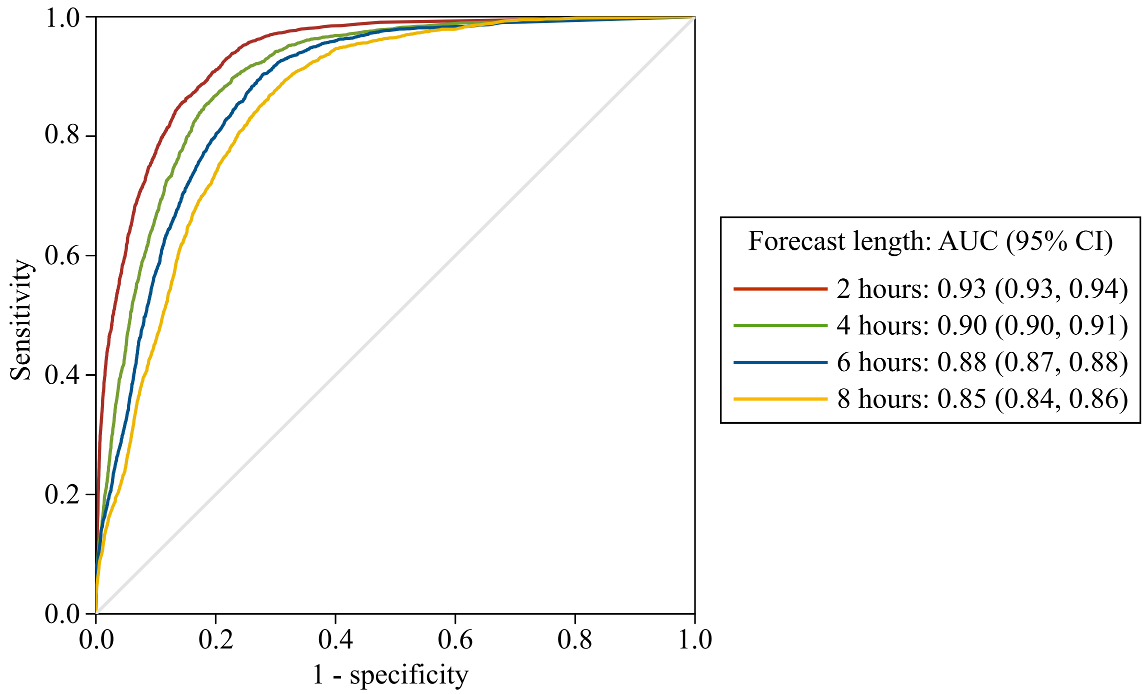

Figure 13. Receiver operating characteristic curves of ambulance diversion forecasts. The AUC with 95% CI is shown in parentheses, describing the discriminatory power at varying time points in the future.

Comment

We have successfully integrated the ForecastED tool with the pre-existing information systems in an adult ED. Our implementation monitors and forecasts ED crowding according to several measures in real time, providing forecasts up to 8 hours into the future through a graphical web interface.

The validation results demonstrate that the ForecastED tool can provide real-time, accurate predictions for a variety of ED crowding measures. Using information from past and present patients, the tool accurately predicted five out of seven outcome measures tested, up to 8 hours into the future. It fared less well in forecasting aspects related to the waiting room, which may suggest the crowding status in the waiting room is more volatile than the crowding status in other parts of the ED workflow. The forecasts of the waiting count and waiting time may be most useful when considered 4 hours or less into the future.

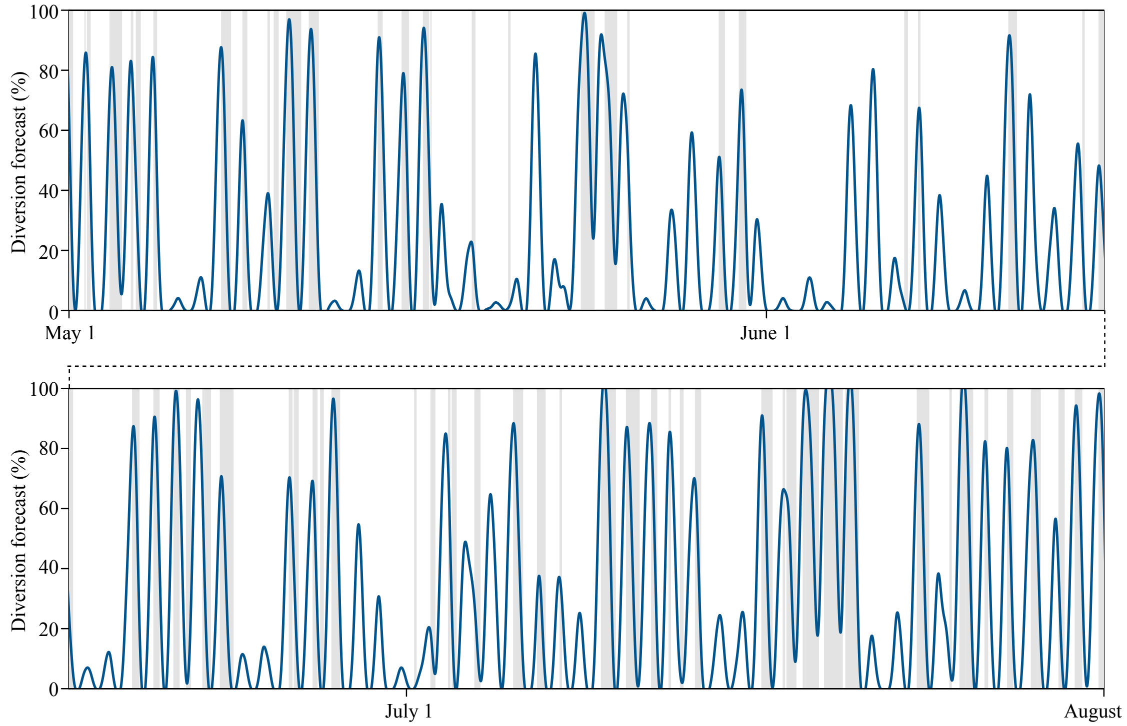

Figure 14. Time series plot of the 6-hour ambulance diversion forecast, 5/1/07 – 8/1/07. The horizontal axis marks the date and time at which the forecast was obtained, and the vertical axis denotes the probability of fulfilling the criteria for ambulance diversion 6 hours into the future from that point. The signal shown here has been smoothed using cubic splines. Episodes of ambulance diversion are marked by the shaded areas.

The results suggested that the forecasts for each continuous outcome measure were well calibrated for all outcome measures except for the boarding time, which showed evidence of a systematic bias. This result was consistent with our previous observations, and a likely mechanism exists within the simulation assumptions that govern allocation of inpatient hospital beds [177]. This issue may be resolved by linearly calibrating the forecasts of boarding time according to the known bias in the residuals.

The results also indicated that the forecasts accurately predicted the probability of future ambulance diversion status up to 8 hours into the future. The time series plot shown in figure 14 illustrates that the predictions closely fit the pattern of ambulance diversion in the study setting, with a peak in the signal immediately preceding most diversion episodes.

One challenge we noted in the prospective implementation and deployment of the ForecastED tool was how to clean patient data in real time. It is standard practice to identify and re-move outlier data, when appropriate justification is provided [179]. We justified the previously stated patient exclusion criteria on the grounds that not all patients recorded in the ED information system participate in the normal ED patient flow. The criteria would be straightforward to apply retrospectively, but not prospectively. For example, a patient with a purely psychiatric complaint would be identified and excluded at the beginning of a retrospective data analysis. However, a patient who is in the waiting room during the prospective study might not be identified, and hence excluded, until after the patient is placed into a dedicated psychiatric bed. Thus, the patient would affect the prospective validation until adequate information existed to mark him or her for exclusion. Although we were unable to eliminate this challenge, the results suggest this does not compromise the utility of the forecasting tool.

The utility of ForecastED depends on a mechanism of instantly disseminating its forecasts to interested parties, so we created a graphical web interface that is updated with every observation. The interface shown in figure 12 illustrates a unique capability of ForecastED: Because a discrete event simulation model fits the pattern of individual patient flow, rather than a specific dependent variable, it can describe crowding from multiple input, throughput, and output perspectives [22]. Thus, it not only warns that an ED will be crowded; it may also pinpoint why the ED will become crowded, which may be different at different times. For example, on a given day crowding may be attributed to a rapid inflow of patients that overload the waiting room, as shown in figure 12. On another day crowding may be caused by large numbers of boarding patients, who remain in the ED for long periods of time while awaiting hospital admission.

Other methods of distributing forecasting results are possible. The tool could interface with a pager system to alert on-call providers of severe crowding, for example, or it could interface with email systems to distribute alerts. The proper method of disseminating warnings of crowding may vary between institutions depending on the local culture and preferences. Any operational change must be tuned to the organizational structure of an institution. Furthermore, some precedent exists for neighboring EDs to share operational data through regional networks [120,180], and this precedent could be applied to achieve local sharing of forecasting results.

This would potentially enhance cooperation in areas with multiple busy tertiary care centers, particularly level 1 trauma centers.

Our study was limited in part because it took place in the adult ED of a single academic institution. Further research will be necessary to determine how well the ForecastED tool will generalize to other settings. No changes should need to be made to the core ForecastED tool when transporting it to other institutions, because it was written in the standard C programming language with no dependencies on external software. The chief alteration required to deploy the tool at other institutions would involve changing the Python integration software that connects to ED information systems, since different institutions have different database storage schemes. Because the software automatically re-calibrates the model parameters every day at midnight, no additional changes should be needed at other sites. Based on local preferences, the tool could also be adapted to forecast outcome measures aside from those used in our study. For example, other institutions are likely to have ambulance diversion criteria that differ from our study setting. No changes would need to be made to the simulation itself, and minor changes would need to be made to the code that processes the simulation output, in order to forecast ambulance diversion according to different criteria. The process of real-time system deployment should be repeatable in any ED that has six required patient-level variables available electronically.

Our study was also limited in part because we made no intervention based on the tool. This allowed us to validate the forecasting accuracy in a live, operational setting; however, the goal of ForecastED is not merely to provide information, but to spur action based on this information to alleviate ED crowding. The question of how interventions triggered by the forecasts would directly impact patient care remains a valuable topic for further research. The possible methods of intervening include just-in-time dynamic resource mobilization within the ED. Few reports have discussed the prospect of allocating personnel and beds on demand [103], perhaps because the technology to determine when to mobilize such resources is generally unavailable. Another possible application of the tool would be to foster improved coordination between an ED and primary care providers, who refer patients for ED care; or between an ED and hospital units, to which the ED admits patients for inpatient care.

In summary, we have deployed and prospectively validated the ForecastED tool, which provides potentially useful forecasts of various ED crowding measures up to 8 hours into the future. In keeping with the principle "you can't manage what you can't measure", this may enable new, proactive strategies for coping with the ED crowding problem. This work may provide a means of protecting and strengthening the fragile safety net of the health care system.

CHAPTER VI

CONCLUSION

Research Summary

My research has been motivated by the crisis of crowding that currently faces emergency departments (ED) in the United States and abroad. The overall goal of the work was to apply knowledge from the fields of queuing theory and discrete event simulation to provide a reliable means of forecasting ED crowding in the near future.

The project began with a systematic review of the literature on ED crowding. Through a broad search of PubMed®, two reviewers identified articles that described causes, effects, and solutions of ED crowding. The study focused on the type of crowding that occurs in a general, everyday setting, rather than the type of crowding that results from uncommon disaster events. A total of 93 articles were included in the review. The causes of crowding included non-urgent visits, frequent-flyer patients, influenza season, inadequate staffing, inpatient boarding, and hospital bed shortages. The effects of crowding included patient mortality, transport delays, treatment delays, ambulance diversion, patient elopement, and financial impact. The solutions of crowding included additional personnel, observation units, hospital bed access, non-urgent referrals, ambulance diversion, destination control, crowding measures, and queuing theory. Two key observations from the systematic literature review guided the remainder of my research: First, several techniques of measuring ED crowding have been proposed [23-28]. Few of them were validated in real time, and none of them were examined for the purpose of forecasting crowding in the near future. Second, only one article was identified that involved just-in-time dynamic resource mobilization to alleviate ED crowding [103]. This may be attributable, at least in part, to the general unavailability of ways to forecast near-future crowding.

The next step of the project involved a prospective validation of four published crowding measures: the Emergency Department Work Index (EDWIN) [24], the National Emergency Department Overcrowding Scale (NEDOCS) [26], the Demand Value of the Real-time Emergency

Analysis of Demand Indicators (READI) [25], and the Work Score [28]. The goal of this study was to validate the ability of these instruments to measure ED crowding in the present and forecast ED crowding in the future. I developed a computer program that interfaced with local ED information systems and automatically calculated the values of all four crowding measures at 10-minute intervals during an eight-week study period. The EDWIN, the NEDOCS, and the Work Score all reflected present ambulance diversion with good accuracy, although none of them exceeded the performance of the occupancy level. All of the measures had difficulty in reflecting future ambulance diversion, and none performed clearly better than the occupancy level. However, it was interesting to note that the READI demand value showed a greater ability to forecast future crowding than to measure present crowding. I presumed this finding might be explained because one of the the READI scores incorporates historical information about the daily pattern of patient arrivals and discharges [25], whereas none of the other measures did. Overall, the findings of this study suggested that some room existed for additional innovation in forecasting ED crowding [158].

The project continued with the design and implementation of a discrete event simulation model of ED patient flow. Many possible modeling strategies could have been adopted to forecast ED crowding, but I believed that a discrete event simulation, based on queuing theory, would represent the non-linear, time-varying aspects of ED operations more naturally than other strategies [32]. The “ForecastED” simulation model was designed by an interdisciplinary team using evidence from the literature, and it was implemented in the C programming language. During the development process, the use of discrete event simulation revealed an additional, previously unforeseen, advantage: The simulation output is not a single, numeric dependent variable; instead, its output is a detailed list of patients projected to be in the ED in the future. Because of this, the simulation is not tied to any particular outcome measure, such as the local ambulance diversion status – it can theoretically be used to forecast any outcome measure of interest. This property of the simulation model implies that it could overcome a widely recognized problem in the field of ED crowding research; namely, that no standard definition exists for what the term “crowding” should imply [31,155]. A preliminary, retrospective validation of the simulation model suggested a reasonable fit for ED patient flow, but it remained to evaluate the tool in a real-time, operational environment.

The final step of the project was the prospective, real-time evaluation of the ForecastED tool. I developed a "wrapper" program in the Python language that integrated the core simulation executable with local ED information systems. The dual purposes of the wrapper program were to maintain the simulation parameters using historical patient data, and to invoke the ForecastED tool using current patient data. The validation took place during a three-month interval, and throughout this time a crowding forecast was updated every 10 minutes. I used the simulation to forecast the waiting count, waiting time, occupancy level, length of stay, boarding count, boarding time, and ambulance diversion up to 8 hours into the future. A graphical web interface presented the results in a manner that may become useful operationally. The system was reliable, with nearly 100% uptime during the study period. The forecasts were accurate for most outcome measures up to 8 hours into the future, except that the forecasts of the waiting count and waiting time may be most useful when considered 4 hours or less into the future. The forecasts of one of the outcome measures, the boarding time, was systematically biased, suggesting that calibration may be an important step during system deployment. This study built upon the theory of the ForecastED tool, providing the necessary proof-of-concept to consider the practical, interventional use of the system.

A few issues have not been addressed during my graduate research, and these may provide valuable opportunities for future work. First, the ForecastED tool was developed and validated at single, academic institution, so my results are not sufficient to describe its generalizability to other settings. This issue is currently the focus of an ongoing collaboration among five institutions spread throughout the United States. Second, my tool has not yet been used to trigger interventions. Although I have provided the necessary technology, substantial additional work must be done regarding organizational and institutional factors to manage the changes in health care delivery. Third, no research has been published to describe the potential impact, in terms of realizable gains, that may be given by a crowding intervention at the Vanderbilt University Medical Center. Fourth, my research must be placed in the proper informatics context, because it depends upon the proliferation of ED information systems to achieve its intended purpose. Two brief sections are warranted to address these last two issues in greater detail.

Potential Impact

In the systematic literature review, ambulance diversion and patient elopement were shown to be adverse consequences of ED crowding [61,64,91-96]. Many outcome measures may be used to express the potential impact of on-demand dynamic resource mobilization, although these two will serve for the present discussion. The purpose of this section is to provide the reader with a frame of reference describing how much gain could be achieved by a timely crowding intervention in the adult ED where this research took place. The ensuing paragraphs describe a secondary analysis of patient data from a 12-month period (9/1/2005 – 9/1/2006), following a previously described protocol [176].

Ambulance diversion has been shown to be a mechanism by which financial opportunity costs are incurred in the form of lost hospital revenue [176]. As shown in figure 15, I calculated

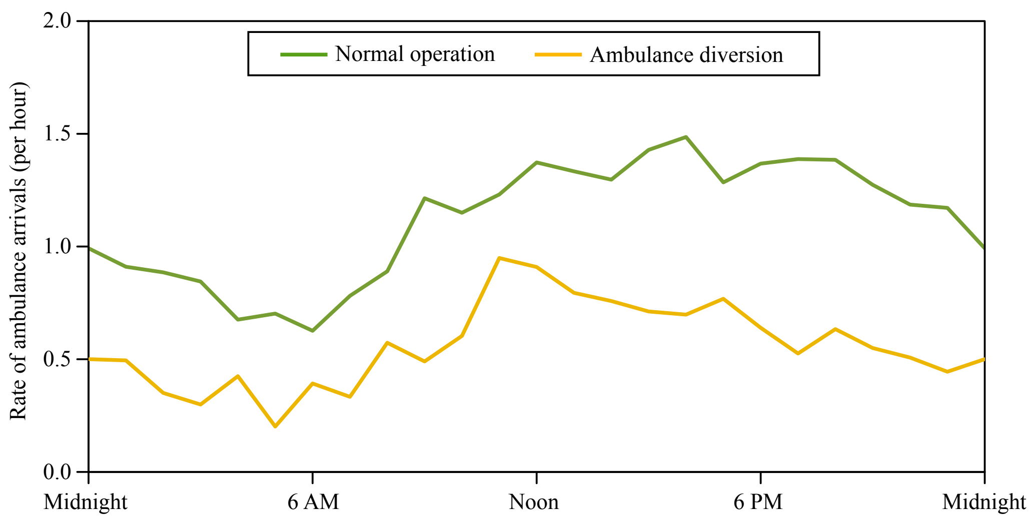

Figure 15. Hourly rate of ambulance arrivals by time of day. The green line denotes the rate of ambulance arrivals during normal operation, and the yellow line denotes the rate of ambulance arrivals during ambulance diversion. The vertical distance between the lines describes the number of ambulances diverted within each hour of the day.

the rate of ambulance arrivals during periods of normal operation and diversion, controlling for the time of day. The vertical distance between the lines denotes the average number of diverted ambulances during each hour of the day. Multiplying the difference in ambulance arrival rates by the total number of diversion hours, adjusted for the time of the day, provides an approximate figure of 1,160 ambulances diverted to nearby institutions during the year. Given that 48% of patients who arrive by ambulance are admitted to the hospital, each bringing an average of $12,686 in collected revenue to the institution, this provides a rough estimate of $7 million revenue lost annually due to ambulance diversion.

Patient elopement, or leaving without being seen, has been shown to be a mechanism by which patient safety may become compromised [94-96]. As shown in figure 16, I calculated the rate of patient elopement during periods of normal operation and ambulance diversion, controlling for the time of day. While ambulance diversion is not a direct mechanism that causes patients to leave without being seen, it serves as a reasonable surrogate for overcrowding. The vertical gap between the lines denotes the number of additional patients, beyond the normally expected baseline, who left without being seen during crowded periods. Controlling for the time of

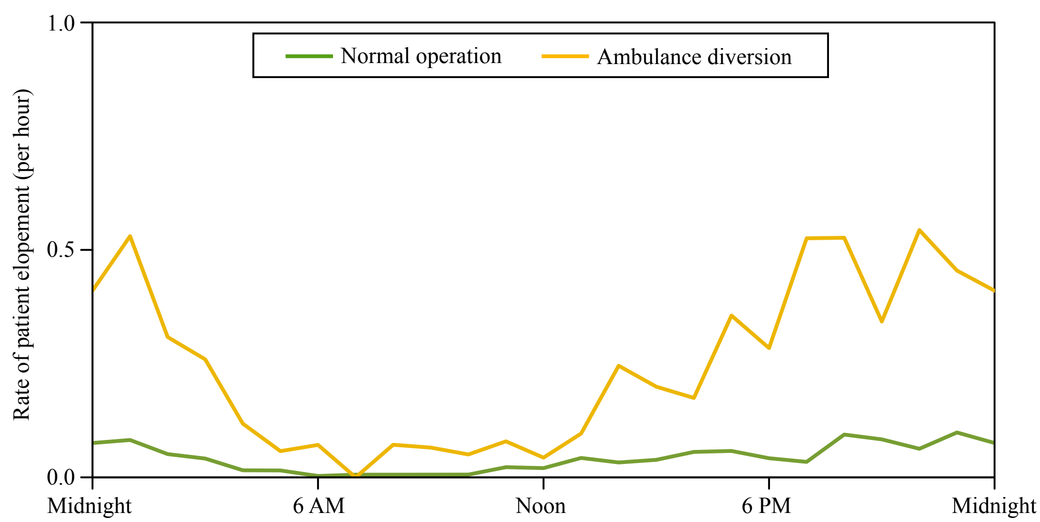

Figure 16. Hourly rate of patients leaving without being seen by time of day. The green line denotes the rate of elopements during normal operation, and the yellow line denotes the rate of elopement during ambulance diversion. The vertical distance between the lines describes the number of additional patients who left without being seen during each hour of the day.

the day and multiplying by the hours of ambulance diversion suggests that 482 patients left without being seen, due to overcrowding throughout the year.

The above figures are intended to provide a crude estimate of how much effect a crowding intervention might have on hospital revenues and patient safety. They must not be construed as a substitute for actual effect sizes, which would need to be measured by an appropriately designed clinical trial. No real-world forecasting system is likely to prevent all crowding episodes at a reasonable cost. Valuable contributions remain to be made through cost-effectiveness analysis, in order to determine the financial viability of on-demand crowding interventions.

Information Systems

The practical value of my research relies on the availability of ED information systems. If the end product of the research were a simple model that could be evaluated using a nomogram or a pocket calculator, this might not have been the case. In keeping with its intended purpose, the ForecastED tool is relatively concise compared with the complex details that others have implemented into discrete event simulations of ED patient flow [33-36,177]. Regardless, forecasting several outcome measures over a large number of simulation replications remains a computationally intensive process. Also, all information required for the tool must be available electronically, in real time, to automate the process of obtaining forecasts. The ForecastED tool has minimal input data requirements by design; however, the data must be available through ED information systems to render its deployment practical.

My research was made possible by a robust information system that was already implemented at Vanderbilt University Medical Center. Nearly all data used for the project were obtained from the databases underlying an electronic whiteboard system, which was developed and implemented in-house. The electronic whiteboard provides a central point of access to many different pieces of data that describe the minute-by-minute operating status of the ED. These data may be visualized using a centralized plasma display or using a standard web browser on any networked computer within the ED. A screenshot of the web interface to the electronic whiteboard is presented in figure 17. Its numerous roles include tracking patients, monitoring safety, and alerting personnel to important issues. This electronic whiteboard system has been shown to benefit the efficiency of communication among health care providers [181]. The ForecastED tool represents just one of many possible innovations that can be achieved by leveraging a solid informatics foundation like the electronic whiteboard system.

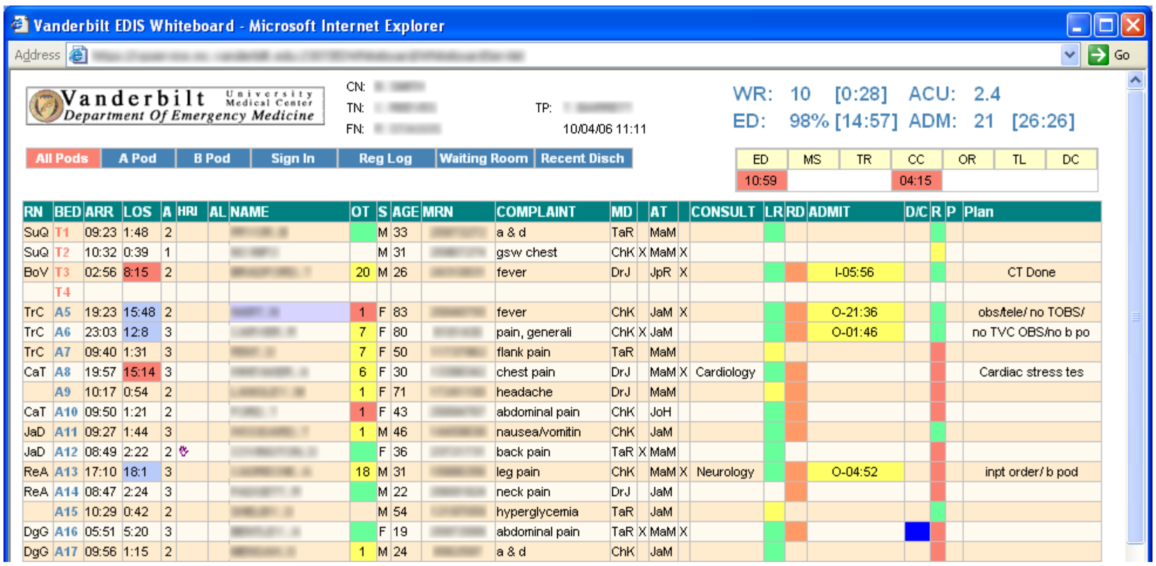

Figure 17. Screenshot of the Vanderbilt University electronic whiteboard system. The system provides real-time patient tracking information to physicians, nurses, technicians, and other end users. Each patient who is presently in the treatment area is listed along with their time of entry, name, chief complaint, attending and resident physicians responsible for care, pending consults, and other fields. Patients in the waiting room are enumerated in another pane, which is not shown here. An operational summary is provided in the upper right, which shows measures such as the waiting room count, average length of stay, mean patient acuity, and diversion status of several hospital services.

Many institutions do not yet have patient tracking systems, similar to the electronic whiteboard, deployed within the ED. I am unaware of any exact numbers that have been published regarding the adoption rate of ED patient tracking systems. However, studies on the prevalence of other kinds of information technology have indicated that billing and financial systems are widespread, but the adoption rate has been slower for systems that relate directly to care delivery, including electronic medical records (EMR) and computerized physician order entry (CPOE) systems [182-183]. Numerous barriers may explain this observation, including resistance to change, lack of clear leadership, poor integration with workflow, and high costs of implementation [184]. Improving patient safety remains at the forefront of the national agenda, and the available evidence shows that information technology improves the efficiency and quality of health care [185]. Many of the above issues likely also apply to the adoption of information systems for patient tracking within the ED. The Centers for Disease Control and Prevention proposed version 1.0 of a standard for ED information systems, called the Data Elements for Emergency Department Systems [186]. The widespread acceptance of DEEDS or a similar standard would likely spur the adoption of information technology among emergency health care providers. The ForecastED system may represent one mechanism by which benefit can accrue through the proliferation of information technology in health care.

Closing Words

This discussion cannot bring closure to the substantial work that remains to properly address the issue of ED crowding. This crisis is deeply rooted in the political and societal aspects of American health care, and substantial cooperation among many stakeholders will be necessary to resolve the issue. My hope is that this research provides a small piece of the complex puzzle that must be solved in order to ensure the access and quality of emergency health care.

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