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System Complexity As a Measure of Safe Capacity for the Emergency Department

Daniel J. France, PhD, MPH, Scott Levin, MS

Abstract

Objectives: System complexity is introduced as a new measure of system state for the emergency department (ED). In its original form, the measure quantifies the uncertainty of demands on system resources. For application in the ED, the measure is being modified to quantify both workload and uncertainty to produce a single integrated measure of system state.

Methods: Complexity is quantified using an information-theoretic or entropic approach developed in manufacturing and operations research. In its original form, complexity is calculated on the basis of four system parameters: 1) the number of resources (clinicians and processing entities such as radiology and laboratory systems), 2) the number of possible work states for each resource, 3) the probability that a resource is in a particular work state, and 4) the probability of queue changes (i.e., where a queue is defined by the number of patients or patient orders being managed by a resource) during a specified time period.

Results: An example is presented to demonstrate how complexity is calculated and interpreted for a simple system composed of three resources (i.e., emergency physicians) managing varying patient loads. The example shows that variation in physician work states and patient queues produces different scores of complexity for each physician. It also illustrates how complexity and workload differ.

Conclusions: System complexity is a viable and technically feasible measurement for monitoring and managing surge capacity in the ED.

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Emergency departments (EDs) are a critical component of our health care infrastructure because they provide essential emergent and urgent care services during ordinary times and rapid response care during times of crisis or disaster. Data published in the Centers for Disease Control and Prevention's 2004 report, *National Hospital Ambulatory Medical Care Survey: 2002 Emergency Department Summary*,¹ indicate that EDs in the United States are quickly losing their reserve capacity due to increasing patient demand and shrinking bed capacity. The Centers for Disease Control and Prevention estimates that between 1992 and 2002, ED visits increased 15%, while the number of hospitals operating EDs de-

creased 23%.¹ U.S. EDs received more than 110 million patient visits in 2002, compared with 89 million in 1992.

The increased production pressures have exposed the nation to the complexities and inefficiencies of the ED system and the ED-hospital interfaces.^{2,3} Frequently, crowding caused by these system factors results in ambulance diversion, increased patient wait times, increased lengths of stay, patient boarding in the ED, and decreased patient satisfaction.^{4–11} Although insufficient research has been conducted to establish a definite link between ED crowding and adverse patient and provider outcomes, there is growing evidence to suggest that such a link is both reasonable and likely.^{12–19} Research has shown that EDs generate high rates of preventable adverse events, risk management claims, and patient complaints.^{13,20–23} Other studies have shown that ED providers experience high levels of workload and stress and high rates of depression and career burnout.^{24–35}

Emergency department systems researchers have largely focused on crowding measures as indicators of system state, despite their recognition that system complexity, as created by patient factors, work process factors, and ED-hospital interface factors, affects provider and system performance.³⁶ Although investigators have made important progress in diagnosing the causes of overcrowding and their effects on ambulance diversion,

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they have not adopted a standard definition of overcrowding or defined standard criteria for diversion.^{36,37} While overcrowding is a critical factor influencing ED safety and efficiency, we assert that it is an inadequate measure of system state for evaluating ED capacity or for the purposes of safety research, operations research, and quality improvement.

In this report, we introduce a measure of system complexity for the ED based on research in manufacturing and information theory. In its current form, it can be used to quantify the uncertainty of the demands on ED resources (i.e., providers and systems). Quantifying uncertainty is especially appealing and important because there is growing evidence that uncertainty as created by variability in patient volume, patient acuity, and inpatient bed availability is one of the major determinants of ED capacity.^{8,38–41} Further, system complexity has the potential to be a truly comprehensive ED system metric compared with crowding measures, such as occupancy or system workload, because it can be modified to include the magnitude of work demands in the ED. This would produce a single integrated measure of ED workload and work uncertainty for the ED.

Another attractive feature of the proposed measure is that it will enable ED system researchers to consider and evaluate the concept of capacity in a new light. Specifically, we believe this measure can be used to show that there is a difference between the efficient (or physical) capacity of an ED and its safe capacity. We define the safe capacity of the system as the capacity at which human performance and the safety of the ED system begins to deteriorate. We believe that under conditions or circumstances of high complexity, the safe capacity can be well below the physical capacity of the ED (i.e., number of staffed beds). Therefore, it is the uncertainty of the ED system at a point in time, in addition to its workload, that ultimately dictates capacity. Finally, because the proposed measure is based on information theory, it will lend itself well to human factors and cognitive systems research (i.e., study of human performance in complex, high-risk domains). Ultimately, we believe this research will improve public health by creating a new framework to study and improve ED safety and efficiency.

SYSTEM COMPLEXITY

Complexity is a fundamental but abstract property of sociotechnical (i.e., man-machine) systems that represents the expense or consequence of increased system functionality, efficiency, or flexibility.⁴² Complexity has been identified as one of the major determinants of susceptibility of high-risk systems to accidents and thus remains a primary focus of modern systems and safety research.^{43,44} Some experts have gone so far as to refer to complexity as the “enemy of very high levels of human-systems performance.”⁴⁵ Leading patient safety researchers have recommended that health care should focus on complexity rather than error.⁴⁶ Similarly, leading ED systems researchers have recently recommended that health care use the techniques of operations management, including queuing theory, to study and model the natural and artificial variabilities within the ED and throughout the ED-hospital system.^{39,47} These recommendations are

in direct alignment with the recommendations put forth by the Institute of Medicine and National Academy of Engineering in their 2005 report, *Building a Better Delivery System*.⁴⁸ That report recommended that health care entities apply methods and tools from engineering disciplines to improve the safety and efficiency of the health care system.

The transition from current qualitative understandings of system complexity toward a quantitative representation of this critical system property is becoming more imperative as the need to improve the efficiency, effectiveness, and safety of EDs grows. A measure or set of measures that would quantify ED system complexity would provide opportunities to analyze and model system and provider performance as a function of system parameters. It would help researchers understand the processes individuals and clinical work teams use to manage complexity. Further, it may improve our ability to control and even predict complexity and its short-term impact on ED crowding, capacity, and safety.

In the past decade, operations researchers and manufacturing engineers have introduced and developed several theoretical measures of complexity of manufacturing systems.^{49–52} These researchers define complexity “as a system characteristic which integrates several key dimensions of the manufacturing environment which include size, variety, concurrency, objectives, information, variability, uncertainty, control, cost and value.”⁵⁰ In manufacturing, complexity has the effect of impeding flow by building ever-bigger obstacles. This has the effect of extending lead times and making operations less predictable.⁵⁰

Managers of supply chains have used an information-based (i.e., entropy) measure of complexity to achieve a better understanding of manufacturing processes and how their complexity creates barriers that disrupt the flow of materials and information between the customer and supplier. The complexity measure has also been used by production line managers to determine which system factors (e.g., queue variability, labor shortages, inefficient inspection processes) contribute most to bottlenecks.⁵⁰ The strength of the measure is that it can actually guide managers and operators to the most appropriate solution to improve the performance of the manufacturing system. For example, one form of complexity, static or structural complexity, is best addressed through the simplification of processes. The other major form of complexity, dynamic or operational complexity, is best reduced by improving management of processes or targeted quality improvement interventions.

METHODS

The information-theoretic approach of manufacturing to quantifying system complexity appears to be very relevant to the study of complexity in the ED. This work is based on Shannon’s mathematical theory of information that uses entropy to quantify uncertainty.^{53,54} A system’s entropy represents the amount of information required to describe or control the state of the system.⁵⁵ The entropic measure of complexity specifically integrates principles from queuing theory with Kolmogorov-Sinai entropy. Complexity $H(s)$ in Equation 1) is the sum of a

system's static and dynamic complexities. Its unit of measure is bits.

$$H(s) = H_{\text{Static}} + H_{\text{Dynamic}} \quad (\text{Equation 1})$$

Static complexity is the measure of the expected amount of information needed to describe the system and its components.^{49,56,57} It is a function of the structure of the system, the variety of subsystems, and strengths of interactions. Specifically, the static complexity of a system (H_{Static}) is determined by the number of resources (M) it has (i.e., people, machines, and so on), the number of possible states (S) for each resource, and the probability p_{ij} that a resource i is in state j at a given point in time.

$$H_{\text{Static}} = - \sum_{i=1}^M \sum_{j=1}^{S_i} p_{ij} \log p_{ij} \quad (\text{Equation 2})$$

In the ED, resources are physicians, staff, and medical equipment or diagnostic devices, and their states may be defined as discrete tasks or specific categories of activity. For example, clinician work states may include tasks such as direct patient care, charting, or teaching. Medical equipment, such as a magnetic resonance imaging scanner, has only two possible work states: in use or not in use. In many practical situations, measuring discrete tasks (states) may become very cumbersome. A solution to this impracticality involves merging states into specific categories or "macro states." All discrete tasks are mapped to a "coarser" set of states.⁵⁷ This method may be translated to the ED by considering a macro state to be all tasks a resource performs on one specific patient. Static complexity can be calculated on the basis of direct observation or other data sources (such as databases) that store information on production demand. In manufacturing, static complexity is generally calculated from administrative databases that store bills of materials, routings, and work centers. Static complexity can be reduced by simplifying work processes, and it also can be planned. Static complexity has predictive capabilities (Equation 2).

Dynamic complexity is the measured (actual) amount of information required for defining the state of the system and is typically calculated on the basis of direct observation and measurements of the system for a given time.^{49,56,57} In manufacturing, it has been shown that observational periods of two to four weeks are sufficient to characterize the properties of the system for the purposes of analysis. The sampling rate and sampling duration required to adequately characterize the intensity and variability of ED workflow have not been determined. Sampling requirements will be different for each ED and will be most dependent on ED type (rural, suburban, urban, teaching, and so on), the degree of information technology integration, and the variability of system demands (i.e., patient volume and acuity) experienced by the ED in the past. EDs equipped with advanced information technology systems will be able to determine the nature of system queues almost entirely through retrospective analyses of electronically stored data. Regardless of the method of acquisition, longer observational periods are recommended to account for seasonal effects.

Dynamic complexity reflects the extra amount of information required for defining the state of the system when it deviates from the expected behavior. It is primarily a function of queues (queue variability or queue changes). In the ED, queues are made up of several different entities. Entities are patients or objects (e.g., laboratory specimens, x-rays) that must be processed for the ED to properly deliver health care. Every resource that is utilized by the ED manages a queue. A physician's queue consists of the number of patients he or she simultaneously manages (i.e., patient volume). A triage nurse's queue consists of the number of patients waiting to be triaged at any given point in time. A laboratory technician's queue consists of the number of laboratory tests ordered and awaiting completion. The measure of dynamic complexity quantifies uncertainty of the demands on the ED resources (Equation 3):

$$H_{\text{Dynamic}} = -P \log_2 P - (1-P) \log_2 (1-P) - (1-P) \left(\sum_{i=1}^{M^q} \sum_{j=1}^{S_i^q} p_{ij}^q \log_2 p_{ij}^q + \sum_{i=1}^{M^b} \sum_{j=1}^{S_i^b} p_{ij}^b \log_2 p_{ij}^b \right) \quad (\text{Equation 3})$$

The variables M , S , i , j , and p in Equation 3 are defined identically as they are for Equation 2.

Dynamic complexity considers both planned and unplanned events. It also separates times that the system is deemed in control from occasions where the system is out of control. For dynamic complexity, (P) becomes the probability of the system being in control, (p^q) becomes the probability of queues of varying length (>1), and (p^b) becomes the probability of Bernoulli-type process such as equipment breakdowns or any other unplanned event that stops entity processing. It should be noted that $S_j^q + S_j^b = S_j$, the number of states at resource (i). Because there is a high degree of uncertainty in emergency medicine, it would be difficult to precisely define when the system is in or out of control.

A useful alternative of this equation is to not define the system control constraints, thus setting (P) in equation 3 to zero (Equation 4). Therefore, the equation simplifies to

$$H_{\text{Dynamic}} = - \left(\sum_{i=1}^{M^q} \sum_{j=1}^{S_i^q} p_{ij}^q \log_2 p_{ij}^q + \sum_{i=1}^{M^b} \sum_{j=1}^{S_i^b} p_{ij}^b \log_2 p_{ij}^b \right) \quad (\text{Equation 4})$$

It is also assumed that capturing variability in queue length for resource (i) when in each state (j) would be unreasonable. However, measuring overall queue length variability and the occurrence of unplanned events for each resource (i) is feasible when small sampling windows are used. The resultant modified equation is further reduced to

$$H_{\text{Dynamic}} = - \left(\sum_{i=1}^{M^q} p_{ij}^q \log_2 p_{ij}^q + \sum_{i=1}^{M^b} p_{ij}^b \log_2 p_{ij}^b \right) \quad (\text{Equation 5})$$

Entropy (i.e., uncertainty) is captured in queue length variability in dynamic complexity as it is captured in state probability in static complexity. Complexity values are increased for systems that have highly variable queue

lengths within a given time frame. Complexity also increases as more unplanned events occur that interrupt processing.

The researchers who have developed these measures suggest that greater levels of controlled complexity can increase system flexibility, increase customer satisfaction, and enable higher product variety in manufacturing.⁴⁹ Further, they suggest that these improvements can generate benefits and value that can outweigh the costs of measuring and managing complexity. Similar benefits may be obtained in emergency medicine first by quantitatively evaluating complexity and then by learning to control and manage it effectively.

EXAMPLE AND DISCUSSION

Conceptualizing the mathematical approach to measuring complexity from the equations listed may be difficult; thus, a simplified numerical example is provided to demonstrate how the proposed measure may be calculated and used for a specific set of resources in the ED. Consider a simple team of three physicians staffing an ED. Each time a patient arrives in the treatment area, a physician is assigned to provide care. When care is complete, the patient is discharged from the ED and either admitted to the hospital or discharged from the entire hospital system. Thus, each physician is managing a set of patients at a single point in time and the queue set is changed every time a patient is either assigned to that physician or is discharged. A patient set at a time point will be considered a physician's queue set. The queue behavior for each of the three physicians over a 180-minute interval can be seen in Figure 1. The numerical values at each step represent the percentage of time each physician is experiencing the corresponding queue relative to the period of time studied. Over the time interval, physician (A), who begins with nine patients, manages a total of 12 patients over the entire time window. Physician (B) begins with only five patients and ends with six, never managing more than seven at any point in time, but sees a total of 11 patients. Physician (C) begins with two and sees a total of five patients. The total number of patients a physician

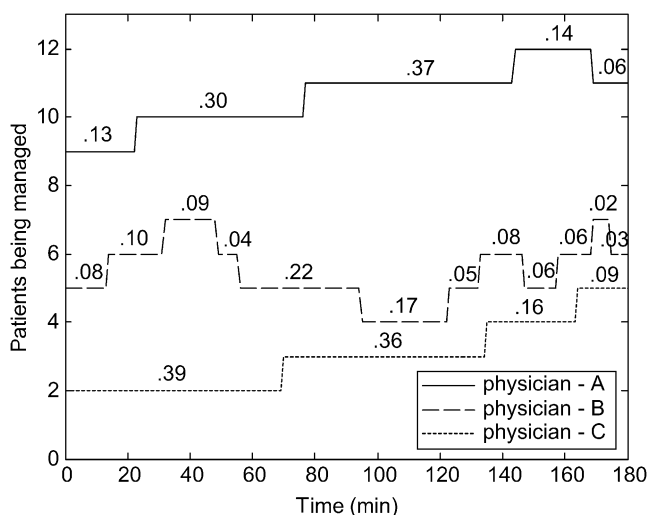


Figure 1. Physician queue behavior.

manages over the time window, and not simply the maximum number managed at any one time, will be called the patient group. Each physician decides how to divide his or her time with each patient within the patient group. The state of a physician at a point in time is determined by which patient the physician is directly managing. All tasks performed for a single patient comprise one macro state of a physician. All tasks that are patient nonspecific comprise an additional macro state of a physician. The distribution of time spent in each state for the three physicians is displayed in Figure 2. The state labeled "N" represents the patient nonspecific state. Examples of patient nonspecific states include paramedic radio calls, gathering ED system data such as waiting room volume and length of stay from an electronic whiteboard, general clinical communications with other emergency medicine providers, and clinical reading. The physician queuing and state behavior is what is needed to quantify complexity.

The static and dynamic complexity for each physician may be calculated. Static complexity is calculated by transforming state time distributions into probability distributions. The probability of a physician resource (i) being in state (j) is

$$p_{ij} = \frac{\text{time in state } j \text{ by each } i\text{th physician}}{\text{total time interval being evaluated}} \quad (\text{Equation 6})$$

Thus, static complexity may be calculated using Equation 2. Dynamic complexity may similarly be calculated by transforming physician queue times into probability distributions. The information provided in Figure 1 may be placed into Equation 5 to render dynamic complexity values for each physician.

The elimination of state dependency (Equation 5) is desirable in that it significantly reduces the amount of information that must be collected. Because ED resources change states quite frequently, we believe this excess information would unnecessarily cloud the measure and make it harder to calculate and interpret. Dynamic

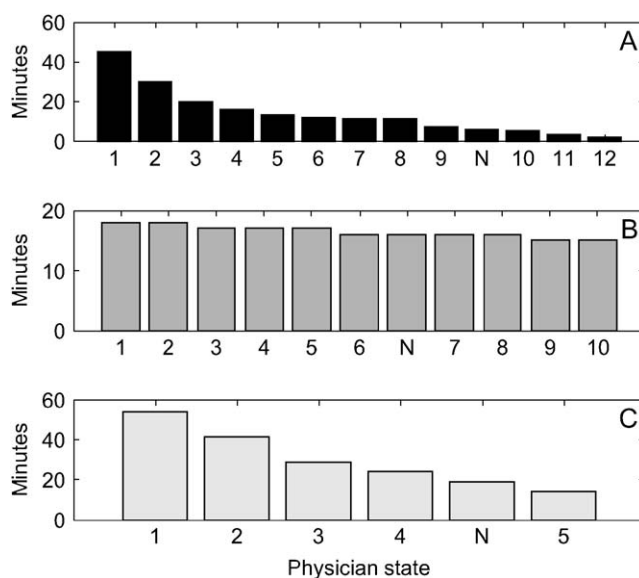


Figure 2. Physician state distribution.

Table 1
Physician Work and Complexity Statistics

Physician	Patients Seen	Average No. of Patients Managed	Average Acuity	Average Workload	Static Complexity	Dynamic Complexity	Total Complexity
A	12	10.59 ± 0.12	2.30 ± 0.01	28.60 ± 0.32	3.27	2.07	5.34
B	11	5.41 ± 0.13	2.29 ± 0.03	14.55 ± 0.30	3.46	3.34	6.80
C	5	2.96 ± 0.14	2.40 ± 0.02	7.71 ± 0.37	2.44	1.79	4.23

complexity may be computed using the information in Figure 1 and Equation 5. The probability of being in each queue (p_i^q) is displayed for each physician in Figure 1. In this example, there were no Bernoulli-type processes; thus, (p_i^p) is set to zero. Examples of Bernoulli-type processes include unexpected loss or failure of system resources, such as when a physician or nurse must leave work due to illness or family emergency or when technological resources such as computed tomographic scanners or laboratory processing systems malfunction. The static and dynamic complexity along with other work statistics are calculated for each physician and displayed in Table 1.

The uncertainty exhibited in queue and state behavior is reflected using the proposed complexity measure. The measure quantifies complexity by capturing both workload and uncertainty. Static complexity effectively incorporates workload by incorporating both the number of patients a physician manages over a given time window and the uncertainty of predicting which patient that physician is delivering care to at any point in time. The static complexity of both physician (A) and physician (B) is greater than physician (C) because they went through significantly more states as a result of seeing more patients. However, physician (B) records a higher value of static complexity by having a more equiprobable (uncertain) state distribution than physician (A) (Figure 2). Dynamic complexity measures the instability of a physicians' queue. Physician (B) records a significantly higher value of dynamic complexity than physician (A) and physician (C) as a result of having a highly transient and unpredictable work queue.

In summary, measuring change and uncertainty in work patterns adds an additional pertinent level of detail to the traditional crowding and workload measures that currently exist to attempt to quantify workload and thus to assess whether physicians are at or near their capacity.³⁶ The value of evaluating change and uncertainty is evident when analyzing the relationship between complexity and conventional measures of system workload.

The measure of physician workload is calculated for each of the three physicians, incorporating the number of patients a physician is managing and the average acuity of the patient set. Triage acuity values are assigned to patients on a scale from 1 to 5, with level 1 being the most severely ill or injured patients. These acuity values are redefined in reverse order to make the workload scores increase when more severe patients present. A low acuity value (1) for a severe patient is redefined as a (5) and so forth. The calculation for workload can be seen in Equation 7:

Workload = number of patients

* reverse order acuity values (Equation 7)

Average acuity, average number of patients being managed, and average workload calculations for each of the three physicians are displayed in Table 1. A comparison on workload versus complexity scores for each physician is displayed in Figure 3. The difference between these measures is evident when looking at physician (A) and physician (B). Physician (A) consistently managed the most patients over time compared with physician (B). Physician (A) also saw slightly more patients than physician (B). The average acuity values for both physicians' patient sets over time were nearly identical. As a result, physician (A) recorded a significantly higher workload value. However, physician (B) recorded a significantly higher complexity value. Physician (B), while never overworked during this period, was operating in the most transient and uncertain environment. The unpredictable nature of physician (B)'s work experience is much more difficult to effectively manage than the other two physicians. This uncertainty is effectively captured in the measure of complexity.

This simple example may be extrapolated to monitor an entire ED system. Measuring the uncertainty of work demands experienced by each system resource will make it possible to calculate a cumulative complexity score for the entire ED system. This will facilitate the identification of workflow bottlenecks and process hazards for clinicians and patients alike that may not be detectable using conventional overcrowding measures. The measure will also provide a means to evaluate the effectiveness of interventions designed to reduce static and dynamic complexity.

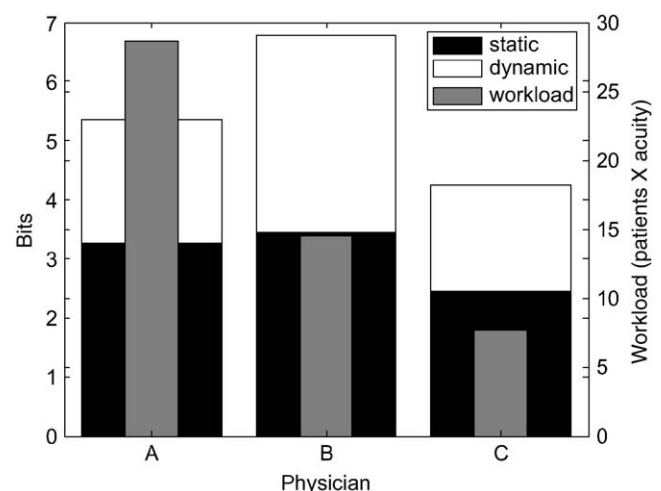


Figure 3. Complexity versus workload.

LIMITATIONS

System complexity shows great promise as a practical measure of system state for the ED. The ultimate value of this proposed measure, however, will be determined by whether it is possible to measure it in real time and use it to monitor and predict the safety and functional capacity of the ED, as well as to potentially mobilize resources or stimulate a decision to go on ambulance diversion, as needed. To achieve this objective, the measure must first be fully adapted to emergency medicine from manufacturing. This would include further modifying the equations for each type of resource in the ED. The equations used in this report to capture complexity in physicians may not be appropriate for nurses or patient care technicians. However, the concept of measuring complexity by incorporating workload and uncertainty must remain the same for each resource included. Monitoring each resource in an analogous fashion enables the ability to calculate a cumulative measure of ED system complexity.

The addition of other system parameters may help further customize the model for emergency medicine. For example, because it is well known that the ED is an “interrupt-driven environment” and that interruptions increase complexity, at least perceptually, it may be useful to add an interruption term to the model (i.e., probability of interruptions occurring in some time period).

Finally, a standard data collection or site sampling methodology must be developed to gather the critical data elements necessary to calculate the measure in a timely manner. Complexity must be measured periodically, perhaps every half-hour, to be an operationally useful measure. Manufacturing engineers have predominantly calculated system complexity on the basis of administrative data and direct observations. This same basic approach can work for emergency medicine. Our preliminary research has determined that modern ED information systems that collect and display system status (e.g., occupancy, patient acuity, physician and nurse patient assignments) collect most of the data necessary to calculate this in near real time.

Even with utilization of such technologies, site-specific sampling, in the form of periodic direct observational studies, will still be necessary to quantify resource utilization patterns. However, rapidly developing indoor positioning systems or electronic tracking systems (such as radio frequency identification) may soon be utilized to perform these observational studies, thus eliminating or minimizing the need for direct human observation.

Emergency departments that are less technologically advanced in terms of ED information systems could rely solely on site-sampling methodologies to calculate complexity in a near-real-time manner. This methodology would follow a similar methodology used by system researchers to calculate and track system workload measure and other indicators for diversion.⁵⁸⁻⁶⁰

CONCLUSIONS

Capacity is a multifaceted construct for all of health care. For an ED, unpredictable surges in patient demand, tight coupling with hospital factors such as inpatient bed avail-

ability, and complex interactions among care providers, patients, and care systems impact the daily surge capacity. Current ED crowding and workflow measures are too simplistic to account for the multidimensionality of surge capacity. As this special topics issue implies, there is a need to develop a science of surge. It is time for ED systems researchers to become innovative in the ways they think about capacity, measure it, and improve it. It is time that we heed the call from expert groups such as the Institute of Medicine and National Academy of Engineering to apply knowledge and methods from other industries to improve the quality and safety of emergency medicine.

Perhaps emergency medicine should follow the lead set forth by the Department of Defense's Operating Room of the Future program. This forward-thinking program, managed by the Telemedicine and Advanced Technologies Research Center (Fort Detrick, MD; available at: <http://www.tatrc.org/>), challenges clinicians and engineers to design and develop tomorrow's operating rooms today by using and integrating the best available technologies, design principles, and evidence-based clinical work processes. The program asks the simple question, “How should modern ORs be designed to maximize the performance of the clinical team and the comfort and safety of their surgical patients?” ED system researchers must adopt this same approach in developing solutions to improve the flexibility and adaptability of ED systems to handle both daily and disaster surge demands.

The objective of this report is to propose a new measure of ED system state that has potential to facilitate innovative thinking and improvement in assessment of the safety and complexity of the ED environment. We suggest a measure of system complexity, as adapted from manufacturing engineering, to quantify the magnitude and uncertainty of work demands on ED resources. By quantifying ED system complexity, the relationship between the safe capacity and physical capacity of an ED can be explored and evaluated. Ideally, system complexity can be used to prospectively track functional capacity and intelligently manage the ED.

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