Hospital Workload and Adverse Events

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Context: Hospitals are under pressure to increase revenue and lower costs, and at the same time, they face dramatic variation in clinical demand.

Objective: We sought to determine the relationship between peak hospital workload and rates of adverse events (AEs).

Methods: A random sample of 24,676 adult patients discharged from the medical/surgical services at 4 US hospitals (2 urban and 2 suburban teaching hospitals) from October 2000 to September 2001 were screened using administrative data, leaving 6841 cases to be reviewed for the presence of AEs. Daily workload for each hospital was characterized by volume, throughput (admissions and discharges), intensity (aggregate DRG weight), and staffing (patient-to-nurse ratios). For volume, we calculated an "enhanced" occupancy rate that accounted for same-day bed occupancy by more than 1 patient. We used Poisson regressions to predict the likelihood of an AE, with control for workload and individual patient complexity, and the effects of clustering.

Results: One urban teaching hospital had enhanced occupancy rates more than 100% for much of the year. At that hospital, admissions and patients per nurse were significantly related to the likelihood of an AE ($P < 0.05$); occupancy rate, discharges, and DRG-weighted census were significant at $P < 0.10$. For example, a 0.1% increase in the patient-to-nurse ratio led to a 28% increase in the AE rate. Results at the other 3 hospitals varied and were mainly non significant.

Conclusions: Hospitals that operate at or over capacity may experience heightened rates of patient safety events and might consider re-engineering the structures of care to respond better during periods of high stress.

Key Words: patient safety, workload, adverse events

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In its reports on medical error, The Institute of Medicine (IOM) stressed the importance of system redesign while calling for improvements in both patient safety and efficiency.[1,2] Although both goals are laudable, the IOM did not address the possibility that achieving 1 goal might be at odds with the other. Hospitals and other providers are under tremendous pressure to maximize revenue while minimizing cost, so that many may be providing more complex care to more patients in busier units with fewer staff. During busy times of the year, some hospitals may become very crowded, in many cases diverting patients to other facilities. When hospitals become full, it is commonplace for patients to wait for long periods in the emergency department or to be cared for in recovery rooms when intensive care beds are unavailable. The likelihood that adverse events (AEs) and related medical errors occur more often during busy times is an idea with intuitive appeal, yet few empirical data are available regarding this in healthcare.

The purpose of this study was to determine the extent to which various measures of hospital workload, measured daily, are associated with the daily rate at which AEs occur. In hospitals, workload is related to patient care activity, which can be characterized by volume, throughput, and case intensity. We hypothesized that the likelihood of AEs in hospitals would increase as workload increased, regardless of the average daily workload in a given institution.

METHODS

Study Period and Data

We defined the study period as the 12 months from October 1, 2000, to September 30, 2001. Four hospitals in 2 states participated in the study: 2 large urban hospitals and 2 smaller suburban teaching hospitals. Data from electronic sources were obtained from the hospitals for the 15-months between October 1, 2000, and December 31, 2001, to allow capture of readmissions containing delayed evidence of AEs

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related to admissions that occurred during the study period (eg, readmission for wound dehiscence following an exploratory laparotomy).

Three main sources of data were used: (1) Administrative data including routine billing/diagnostic records to select the sample, to obtain counts of admissions and discharges, and to obtain patient age, sex, and DRG; (2) Other hospital administrative data on nurse staffing levels and bed counts; and (3) medical record review to identify AEs.

Sample and Sample Screening

The eligible population included 58,143 discharges from the acute medical and surgical services of the study hospitals (Table 1). To limit the number of chart reviews, we used administrative data screens to identify cases with a higher than average likelihood of an AE. We combined screens from Bates,[3] the Complication Screening Program (CSP),[4] and AHRQ's Patient Safety Indicators (PSIs), using PSIs that did not overlap with the CSP.[5] Based upon an expected 28% screen positive rate,[3] we randomly selected 24,676 discharges, (42.4% of eligible discharges) as the analytic sample for this study. The sample size was based on the estimated number of AEs we expected to find and was designed to have sufficient power to detect a 30% increase (Rate Ratio = 1.3) in the rate of AEs comparing days of high workload to days of low workload. The analytic sample included both patients who screened positively for AEs, ie, "screen positive" cases (n = 6841; 27.7%), and "screen negative" cases (n = 17,835; 72.3%). All screen positive cases underwent chart review. Additional reviews of readmissions brought the total number of charts reviewed to more than 8000.

Most medical records for "screen negative" cases were not reviewed, and were treated as cases without an AE. Only "screen positive" cases with a confirmed AE via chart review were counted as having an AE for purposes of analysis. This was a conservative assumption, since a small validation study found "screen negative" cases to have AEs at about half the rate as the "screen positive" cases.

Dependent Variables: Detection of Adverse Events

An AE is an injury secondary to medical care and not a result of a patient's underlying medical condition. An error occurs when a planned action is not completed as intended or an incorrect plan is used. Errors often do not result in patient injury.[1,2] We focused on AEs rather than errors because most errors are not reported in charts and many AEs that are not associated with an error may still represent important quality problems.

A prespecified list of 18 AEs (Table 2), with 1 additional category for all others, was created based upon previous work.[6] We included AEs that were common, potentially preventable, potentially severe, and identifiable using chart review. To increase the reliability of case identification, explicit evidence-based definitions were created, where possible. Case definitions for infections were obtained from the Center for Disease Control's National Nosocomial Infections Surveillance System.[7] The definitions for postoperative myocardial infarction were based on the American Heart Association's guidelines; and the definitions for surgical complications, thromboembolic complications, falls, pressure sores, adverse drug events, and iatrogenic pneumothorax were guided by the literature.[8–18]

We used a 2-tiered method for identifying AEs.[19–21] Trained RNs with clinical and chart review experience reviewed all selected medical records, identified whether an AE may have occurred using the case definitions, and if so, prepared case summaries for the physicians. Two physician-reviewers then independently verified the event, and scored the severity, preventability, and their confidence that the event was due to medical management and not the disease process. The physician reviewers conferenced with each other to discuss disagreements and came to consensus; no cases required a third reviewer for unresolved disagreements. The nurses underwent 2 days of training, which included an overview of the study, definition of terms, review and practice with the data tools, and discussion of examples of AEs. Physician reviewers underwent a similar, although less intensive, training.

We developed 2 computerized tools to improve data capture and to facilitate communication with physician reviewers. One tool was developed for nurse abstractors to use in AE identification and incorporated rule sets with criteria to define AEs. A second tool was developed to collate and distribute case summaries for physician review.

TABLE 1. Study Sample, Numbers Screened, and AEs Found, by Hospital

	Hospital				
	A	B	C	D	All
Adult medical-surgical patients eligible for screening during study period	28,248	14,693	6456	8746	58,143
Sample selected for study	8499	7414	3866	4897	24,676
Screen positive cases selected (all were reviewed)	2504	2137	960	1240	6841
As % of study sample	29.5%	28.8%	24.8%	25.3%	27.7%
AEs from chart review	721	482	120	207	1530
AEs per 100 patient days	1.21	1.08	0.50	0.68	0.98

Note: Hospitals A and B were major urban teaching; Hospitals C and D were suburban teaching.
More than one AE could have been detected per patient.

TABLE 2. AEs Identified During Chart Review

			Hospital							
	Total		A		B		C		D	
AE Type	**N**	**%**	**n**	**%**	**n**	**%**	**n**	**%**	**n**	**%**
1. Wound infection	193	12.5	80	11.0	73	15.1	18	15.0	22	10.5
2. Hospital-acquired urinary tract infection	125	8.1	48	6.6	37	7.6	22	18.3	18	8.6
3. Hospital-acquired pneumonia	84	5.5	31	4.3	19	3.9	14	11.7	20	9.6
4. Hospital-acquired bacteremia	19	1.2	10	1.4	6	1.2	1	0.8	2	1.0
5. Hospital-acquired sepsis	25	1.6	12	1.7	7	1.4	4	3.3	2	1.0
6. Operative nerve injury	21	1.4	11	1.5	7	1.4	2	1.7	1	0.5
7. Operative organ injury	54	3.5	20	2.8	17	3.5	10	8.3	7	3.3
8. Operative vessel injury or hemorrhage	136	8.8	80	11.0	50	10.3	5	4.2	1	0.5
9. Postoperative acute myocardial infarction	59	3.8	32	4.4	16	3.3	3	2.5	8	3.8
10. Postoperative stroke	49	3.2	30	4.1	17	3.5	1	0.8	1	0.5
11. Postoperative shock	11	0.7	2	0.3	9	1.9	7	5.8	9	4.3
12. Postoperative respiratory distress or failure	97	6.3	42	5.8	39	8.0	0	0.0	0	0.0
13. Iatrogenic pneumothorax	32	2.1	16	2.2	7	1.4	1	0.8	8	3.8
14. Hospital-acquired pulmonary embolism	33	2.1	14	1.9	13	2.7	1	0.8	5	2.4
15. Hospital-acquired deep venous thrombosis	84	5.5	59	8.1	16	3.3	4	3.3	5	2.4
16. Fall	69	4.5	36	5.0	9	1.9	12	10.0	12	5.7
17. Pressure sore	39	2.5	17	2.3	8	1.6	1	0.8	13	6.2
18. Adverse drug event	309	20.1	140	19.3	99	20.4	12	10.0	58	27.8
19. Other AE not specified above	100	6.5	45	6.2	36	7.4	2	1.7	17	8.1
	1539	100.0	725	100.0	485	100.0	120	100.0	209	100.0

Note: Hospitals A and B were major urban teaching; Hospitals C and D were suburban teaching. Nine AEs were not included in the analyses because of questionable dates of occurrence.

The final step in the review was to assign a time period during which the AE most probably occurred. This time period was not necessarily the same as when an AE was first documented (eg, when a positive blood culture result is reported or a computed tomography scan was ordered). To maximize reliability, we implemented several strategies. Nurse reviewers were asked to provide critical dates that might help with assignment. These dates included, for example, the date of the most recent surgery, a note in the record by a physician when an event or condition first appeared, a witnessed aspiration, or intubation. Furthermore, one of the investigators with experience in detection of AEs (J.M.R.) devised guidelines based upon the known temporal relationship between clinical identification of AEs and the time of AE occurrence. The protocol allowed AEs to be assigned either a single date or a date range. All AEs with date ranges were reviewed by the same investigator. In most cases, the range was only 2 days, but in some cases it was longer, such as for deep vein thrombosis or pulmonary embolism. For example, for postoperative thromboembolic complications the range of AE assignment was from the time of surgery until the first documented clinical signs or diagnostic evidence of the complication. For purposes of analysis, dates with ranges were assigned the midpoint. To test the robustness of our assignment, we repeated our analyses using alternative methods of assignment, including the first date of the range, or assigning all AEs to the date of admission (with the theory that care on the first day is the most important). We also repeated the analyses according to whether or not the admission involved a procedure, and whether or not the AE was judged by the physician reviewers to be preventable. None of these analyses changed our findings qualitatively, although in some cases the significant findings became nonsignificant due to reduced power (fewer events). Therefore, we report only the results from the main analysis, using a midpoint range of the assigned dates.

Reliability Testing

We assessed the performance of our chart review methods in 3 ways. First, we abstracted a random sample of 1990 screen negative charts and found 1774 admissions had no AEs (true negative) and 216 admissions (11%) contained AEs (false negative). Thus, the sensitivity and specificity of our screening tool was 0.44 and 0.75, respectively. Second, using a random sample of screen positive charts, we tested the intrarater reliability among nurse abstractors and inter-rater reliability between nurse and physician reviewers. The intraclass correlation (ICC) among nurses was good to excellent (ICC = 0.61 and 0.96 at the central and distant study sites, respectively). Inter-rater reliability was conducted at the central study site between nurses and physician, and also was good (kappa = 0.69). Lastly we tested the reliability of physician rating for AE classification, severity and preventability. Using random samples of event case summaries, our IRR for event classification (kappa = 0.69), event severity (kappa = 0.67) and preventability (kappa = 0.50) were comparable to prior AE studies using physician chart review and adverse drug event studies using case summaries.[22,23]

Independent Variables: Predictors of Adverse Events

Individual Patient Risk

We controlled for certain patient characteristics that were known or suspected to be confounded with the likelihood of individual patients experiencing AEs. These included age, sex, and case complexity as signified by DRG weights from the Centers for Medicare and Medicaid Services (CMS). However, to avoid adjusting for the complication we were trying to measure, we used the collapsed (adjacent) DRG categories that are separated by the presence or absence of comorbidities or complications. This same approach is used in the Patient Safety Indicator software.[5] In addition, we identified the day of the week, and whether the patient was an emergent or elective admission.

Workload and Staffing

We identified 3 measurable attributes of hospital activity or workload (volume, throughput, and intensity) that are more or less out of the control of hospital administration in the short term, and 2 measures of workload (weekday admission, elective admissions) that are more amenable to short-term management.

Our primary measure of volume was occupancy rate, defined as the number of patients per available (operating) beds. Most hospitals count daily census as the number of patients at midnight. However, this undercounts the workload pressure for high occupancy hospitals that often discharge patients in the morning and admit a different patient later in the day in the same bed. By tracking patient locations using administrative records, we accounted for this "enhanced occupancy," which was about 10% higher than the unenhanced rate and exceeded 100% for some hospitals on some days. In addition, we measured hospital diversion days, but in preliminary analyses diversion was not a significant predictor of AEs and so was dropped from the analysis.

Throughput or turnover refers to the rate at which patients move through the system during a specified period. Two units with equal occupancy rates may have very different admission/discharge turnover. Furthermore, conversations with hospital nurses suggested that the services required for admitting or discharging patients are greater on average than for patients already in the unit. Thus, we measured admissions per day and discharges per day.

Intensity refers to the case complexity or severity of illness of all the patients being cared for in a particular location. Hospital workload increases with sicker patients, and thus may increase the likelihood of AEs independent of a patient's individual case complexity. On each day, we calculated a severity-weighted census, defined as the sum of the DRG weights for all patients in each hospital location on each day. For this variable, we used the actual DRG, not the "adjacent" version used to assess individual risk. We considered the use of nursing acuity measures, but at the time of the study these were available only at a single hospital, so we dropped them from the analysis.

Staffing data were requested for each unit and hospital for each day of the study period. Although we explored numerous measures, in the end we used the patient to nurse ratio, since it has been shown in previous research to be related to patient safety.[24]

Patient Location and Level of Aggregation

We requested both hospital-level and unit-level workload and staffing information for each day of the study period. Hospital-level data included information for the entire hospital (all medical-surgical units, all Ob/Gyn units, inpatient psychiatric units, etc.). Because of difficulties tracking specific units in the hospitals (units opening and closing during the study period, changing names, and inconsistencies and disagreements among hospital records for workload, staffing, and discharge data), we collapsed data from all adult medical-surgical units into 2 "superunits," intensive care unit (ICU) and non-ICU.

Analysis

The main focus of our analysis was the relationship between variation in daily workload and AEs. All analyses were conducted using Stata (Version 8, http://www.stata.com/). The goal was to determine whether AEs were more likely to occur on higher workload days over the course of 1 year. Because we had only 4 hospitals in the study, we could not test whether AEs were more common at busier hospitals, overall. Rather the focus was on day-to-day variation within a given hospital. Similarly, although we examined day-to-day variation in patients per nurse, we did not test the hypothesis that hospital staffing levels and AEs are related, per se, also because of the limited number of facilities. Rather, we examined the extent to which daily variations in patient volume per nurse affected the rate of AEs.

In our main analysis, the patient day was the unit of analysis. The dependent variable was the likelihood of an AE for a particular patient on a particular day. Because patients could have more than one AE per day, we used Poisson regressions, which are suited to counted data.[25] We used generalized estimating equations (GEE) and accounted for clustering of AEs within individual patient stays. We estimated 2 models. Model 1 controlled for individual patient risk, including age, sex, and "adjacent" DRG categories. We included whether the patient was being treated in the ICU on the day of the AE, because prior research indicates that the rate of AEs is higher in ICUs.[26] Because various measures of workload are correlated, a separate regression was estimated for each workload predictor, entered as a single independent variable. Thus, 5 separate regressions were estimated, testing the effects of occupancy rate, admissions, discharges, patients per nurse, and aggregate intensity (the DRG-weighted census). In model 2 we controlled for the same variables as model 1, as well as characteristics of the admission that are both correlated with workload and are somewhat modifiable by the hospital, including the day of the week, and whether the patient was admitted electively (vs. emergently). Here again we estimated 5 regressions, one for each workload variable.

Alternative Analyses to Test Robustness of Our Results

Initially we analyzed all 4 hospitals together, using dummy variables for site and with each workload variable standardized to the hospital's mean and standard deviation values. However, few results from the combined analysis were significant. Because crude, unadjusted analyses suggested unique behaviors by each hospital, we present hospital-specific results in this article.

Second, patients often move between ICU and non-ICU settings during the course of their hospitalization, according to changing care needs. Thus, our primary analyses included both ICU and non-ICU locations, using a dummy variable to represent the effect. Subanalyses were performed for ICU and non-ICU locations, separately. However, it is difficult to determine a patient's precise unit location at the time of experiencing an AE. Transfers to an ICU may occur as a consequence of, or a prelude to, an AE. Hence, these analyses were not considered definitive evaluations of the relationship between ICU and non-ICU workload conditions and the frequency of AEs, and thus we do not report them here.

Third, we performed an additional analysis to examine whether a nonlinear representation of the effect of workload would provide different results. To do this, we calculated quartiles for each workload measure and then reran the regressions entering indicator variables for each quartile, using the lowest quartile as the reference group.

RESULTS

Among the 6841 admissions undergoing chart review, we found 1530 AEs (Table 1) which, when applied to the total analytic sample, amounted to 0.98 AEs per 100 patient days in the hospital, overall. Table 2 provides a breakdown of the types of AEs detected. As in other studies,[8] adverse drug events and wound infections were the most common type of event. Table 3 provides characteristics of the study hospitals. Compared with the suburban teaching hospitals, the 2 urban major teaching hospitals had higher numbers of minority patients, fewer Medicare patients, and fewer patients 65 years of age and older. These hospitals also had higher enhanced occupancy rates and numbers of admissions. In particular, Hospital A was more than 100% filled for more than one-quarter of the year. Its median and mean enhanced occupancy rates were considerably higher than the other hospitals. Patient-nurse ratios were available only for Hospitals A and D, and were lower in Hospital A. This discrepancy was likely due to Hospital A's more complex case mix, general staffing patterns, and the difficulty in distinguishing noncaregiver staff, eg, nurse directors and instructors, from licensed staff, in the data provided to us. Because the number of noncaregivers tends to be constant day-to-day, they do not affect the analyses.

Table 4 presents the results of our multivariate models. Few of the results are significant except for Hospital A, the large urban teaching hospital with very high occupancy rates. For Hospital B, only admissions per day was significant in model 1, and only discharges per day was significant in model 2, although it appears as if higher numbers of discharges were related to *fewer* AEs, which was contrary to our hypothesis. For Hospital C, there were no significant results for any of the models. For Hospital D, only the occupancy

TABLE 3. Study Hospital Characteristics

	Hospital			
	A	**B**	**C**	**D**
Type of hospital	Major Teaching	Major Teaching	Suburban Teaching	Suburban Teaching
Race				
White	78.1%	87.3%	95.6%	92.2%
Nonwhite	21.9%	12.7%	4.4%	7.8%
Gender				
Male	50.6%	49.4%	37.4%	42.0%
Female	49.4%	50.6%	62.6%	58.0%
Payer				
Medicare	33.9%	41.9%	55.1%	47.3%
Private	47.9%	N/A	39.3%	42.5%
Other	18.20%	58.1%*	5.6%	10.2%
Age, yrs				
<65	61.30%	59.60%	43.30%	36.30%
65+	38.70%	40.40%	56.70%	63.70%
"Enhanced" occupancy rates				
25th percentile	90%	81%	55%	75%
50th percentile (median)	97%	88%	62%	82%
75th percentile	103%	95%	70%	87%
90th percentile	106%	100%	77%	90%
Admissions				
25th percentile	70	44	15	25
50th percentile (median)	117	62	20	30
75th percentile	129	71	25	35
90th percentile	136	79	30	39
Discharges				
25th percentile	89	52	16	24
50th percentile (median)	108	59	20	30
75th percentile	124	66	25	35
90th percentile	133	73	29	40
Patients per nurse				
25th percentile	2.0	N/A	N/A	5.1
50th percentile (median)	2.1	N/A	N/A	5.3
75th percentile	2.2	N/A	N/A	5.5
90th percentile	2.3	N/A	N/A	5.7
DRG-weighted census				
25th percentile	1606	630	114	162
50th percentile (median)	1703	675	130	181
75th percentile	1803	726	151	198
90th percentile	1876	762	170	210

*Includes private.

"Enhanced" occupancy rates account for same-day bed occupancy by more than 1 patient.

Differences among hospitals of mean values for all variables are statistically significant at $P < 0.001$.

N/A indicates not available.

TABLE 4. Relation of Hospital Workload to Risk of Adverse Events: Poisson Regression with Control for Patient Clustering

		Model 1			Model 2		
Hospital	**Workload Variables**	**Beta Coefficient**	**RR**	***P***	**Beta Coefficient**	**RR**	***P***
A	Occupancy rate*	2.50	12.2	<0.001	1.4325	4.19	0.08
	Admissions	0.008	1.008	<0.001	0.0054	1.01	0.03
	Discharges	0.008	1.008	<0.001	0.0055	1.01	0.06
	Patients per nurse	2.42	11.2	0.02	2.4498	11.59	0.01
	DRG-weighted census	0.001	1.001	0.001	0.0006	1.0006	0.09
B	Occupancy rate*	0.64	1.895	0.25	−0.842	0.431	0.22
	Admissions	0.011	1.011	<0.001	0.0004	1.0004	0.93
	Discharges	−0.001	0.999	0.80	−0.0138	0.99	0.01
	Patients per nurse†	—	—	—	—	—	—
	DRG-weighted census	0.0003	1.0003	0.69	−0.0011	0.999	0.14
C	Occupancy rate*	−0.216	0.806	0.82	−0.6803	0.5065	0.52
	Admissions	0.023	1.023	0.13	0.0143	1.014	0.46
	Discharges	−0.004	0.996	0.83	−0.0138	0.986	0.48
	Patients per nurse†	—	—	—	—	—	—
	DRG-weighted census	−0.001	0.999	0.79	−0.0034	0.999	0.49
D	Occupancy rate*	2.45	11.553	0.02	1.703	5.489	0.22
	Admissions	0.015	1.015	0.17	0.0003	1.0003	0.98
	Discharges	0.016	1.016	0.11	0.0021	1.002	0.88
	Patients per nurse	1.16	3.194	0.26	0.5352	1.708	0.61
	DRG-weighted census	0.004	1.004	0.15	0.0014	1.0014	0.64

Hospitals A and B were major urban teaching; Hospitals C and D were suburban teaching.

Occupancy rates are "enhanced," ie, they account for same-day bed occupancy by more than 1 patient. "Admissions" and "Discharges" refer to admissions per day and discharges per day, respectively

*Occupancy rate ratios range from 0 to 1.

†Patients per nurse could not be calculated for hospital B or C.

Model 1: A Poisson regression of the effect of workload on the rate of adverse events. Five separate equations were estimated, with one workload variable entered as an independent variable in each regression. Each regression controlled for patient-level variables of age, sex, adjacent DRGs, and ICU location.

Model 2: Same as Model 1, but with additional control for elective/emergent admission, and day of the week.

RR, risk ratios indicate the relative risk over a 1 unit change in the variable of interest.

rate was significant in model 1. Several of the coefficients for Hospitals B, C, and D were negative (but not significant), suggesting an inverse relationship between workload and AEs. Thus, it is unlikely that increased power would have supported our original hypotheses for these hospitals.

Hospital A, on the other hand, had positive and strongly significant results supporting the hypothesis that increased workload was associated with an increased risk of AEs. All *P* values were 0.015 or less for model 1, which controls for the individual risk variables (age, sex, DRG, and ICU). In Model 2, which adds day of the week and elective/emergent admission, patients per nurse and the number of admissions were both significant at the $P < 0.05$ level, occupancy rate, discharges, and DRG-weighted census were all significant at $P < 0.10$. This can be interpreted as saying that an increase in the occupancy rate of 10 percentage points increases the rate of an AE by 15%, while a 0.1 increase in the ratio of patients to nurse staff increases the rate of an AE by 28%. When we repeated the analyses using indicator variables to represent quartiles of the workload variables, we found our results to be consistent across analyses.

DISCUSSION

We reviewed charts for more than 6800 patients admitted at 4 hospitals, and at 3 of the 4 hospitals, including 1 major teaching hospital and 2 community teaching hospitals, we found no peak workload effect. However, at the fourth hospital, a major urban teaching hospital with very high ambient occupancy rates, the daily variation in number of admissions and patient to nurse ratios was strongly associated with the occurrence of AEs. The explanation for this pattern of events is suggested by Perrow in his classic text, *Normal Accidents*, where he argues that organizations with tight coupling and high complexity (such as hospitals) are more accident prone.[27] Coupling refers to the amount of buffering or redundancy built into the system. Rudolph and Repenning extend the theory to include the effect of "slack."[28] Processes of care work less well when there is little slack in the system, because the system loses its resilience to additional interruptions. Thus, as slack declines, coupling becomes even tighter.

The finding that a 10% increase in occupancy increased the risk of AEs by 15% in the very busy hospital is strikingly similar to the increased risk of death associated with emergency department overcrowding as identified recently in studies of Australian tertiary hospitals operating at similar mean occupancies.[29,30] An increase in AEs associated with crowding is a plausible mediator of the relationship between overcrowding and increased mortality.[31] However, given that this phenomenon represented the experience of only one of our study hospitals, our results are at most suggestive of this chain of events in the United States.

What might this mean for hospital patient safety? Although most hospitals may have sufficient slack to accommodate variations in workload, hospitals that operate at or near capacity on a regular basis should examine their safety data, and if they find a correlation with workload, might consider re-engineering their structures of care to respond better during periods of high stress.[1] Hospital administrators may decide to allow nursing supervisors more leeway in setting staffing levels, or to institute policies that accommodate a larger on-call pool to "flex up" to the required number of nurses. At other hospitals, our results imply that there still might be excess capacity and that enough resources are available so that they can function safely during peak periods.[32]

Our study also has implications for future research. One possibility is to explore the root causes of errors that occur on busy days, investigating, for example, the interaction between crowding, coordination and teamwork. Our results also have implications for on-going research into improvements in patient safety. It is likely that most interventions under investigation are designed for average activity levels, not for periods of high volume. If so, perhaps researchers should consider how the processes they are testing function under conditions of heightened workload pressure.

This study has certain limitations. First, we performed the study at only 4 hospitals, and only one exhibited a relationship between AEs and workload. However, to test hypotheses related to daily variations in AE rates requires performing thousands of chart reviews, which is laborious and expensive, so it is difficult to imagine this study being easily replicated. Computerized detection tools that use event monitoring and natural language processing[33–37] offer the best long-term solution if the same methodology can be expanded to identify other types of AEs. Second, our ability to assign an AE to a single date was limited. Even with the benefit of a root cause analysis, not all complications can be dated with complete confidence, although we instituted a number of strategies to do so. However, such a limitation would tend to make our results conservative. Third, the sensitivity and specificity of our administrative screen was suboptimal and may have caused us to miss AEs, especially minor ones, which could have changed our findings. The performance of the screen may also have varied by type of AE, although it is unlikely that certain types of AEs were differentially screened positive on high workload days versus low workload days. Finally, with our limited sample of hospitals, we were unable to test for a threshold effect where workload triggers an increase in AE rates.

In efforts to compete in an increasingly cost conscious environment, hospitals have pursued a number of strategies to limit costs and increase revenue. Some now operate at or near maximum capacity, with increasing patient to nurse ratios. We conclude that high workload was associated with higher risk of AEs at the largest, busiest study hospital, but not at the other three. These data suggest that high workload may be risky at organizations with little slack, and suggest that administrators should adopt an array of measures to try to minimize risk under these circumstances.

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