Probability of Severe Adverse Events as a Function of Hospital Occupancy

Justin Boyle, Kathryn Zeitz, Richard Hoffman, Sankalp Khanna, and John Beltrame

***Abstract*—A unique application of regression modeling is described to compare hospital bed occupancy with reported severe adverse events amongst inpatients. The probabilities of the occurrence of adverse events as a function of hospital occupancy are calculated using logistic and multinomial regression models. All models indicate that higher occupancy rates lead to an increase in adverse events. The analysis identified that at an occupancy level of 100%, there is a 22% chance of *one* severe event occurring and a 28% chance of *at least one* severe event occurring. This modeling contributes evidence toward the management of hospital occupancy to benefit patient outcomes.**

***Index Terms*—Biomedical informatics, hospitals, prediction algorithms, regression analysis.**

I. Introduction

In many countries, demand for hospital beds has increased through an increased population, increased elderly numbers, increased community expectations, increased provision of hospital services, and a higher availability of therapeutic interventions [1]. There are pressures that all hospitals face to match this demand with available beds in order to get unwell patients into hospital beds in a timely manner. This activity has become more challenging in that the demand increases have taken place in finite capacity health systems, where bed stocks and staff resources have remained fairly constant on a per-capita basis [1], [2].

The focus of recent policy by many governments has been to improve access to beds and reduce waiting times for people requiring hospital care (e.g., [3], [4]). Performance targets related to patient access as well as revenue targets contribute to pressures on hospitals to maximize the utilization of beds.

An alternate view in the face of such pressures is that patient safety is compromised when hospital beds are filled to capacity [5]. However, the evidence around this—specifically whether higher inpatient occupancy equates to a higher likelihood of an adverse event, is minimal. There has been a strong articulation of the need to use patient outcome measures rather than process measures to judge health system function [6] as well as requests for evidence-based debate on this issue [5]–[8].

There have been numerous studies assessing the impact of emergency department, patient safety, and patient flow [2], but research on the effect of occupancy on the safety of patients admitted to hospital beds is scant.

Sprivulis *et al.* [9] looked at the effect that hospital occupancy has on admission times for people waiting in the emergency department and their subsequent mortality. The authors found that increased hospital occupancy led to longer waiting times within the emergency department and an increase in mortality at days 2 and 7. An 85% occupancy rate is the suggested target occupancy by Sprivulis *et al.* to allow for "efficient inpatient flow" and minimize access block-related mortality [9].

In a study of four hospitals over 12 months, Weissman *et al.* [10] found that the rate of adverse events in one hospital was affected by the number of admissions for the day and the patient to nurse ratio. However, the other variables assessed—occupancy rate, the number of discharges for the day, and diagnosis related groups (to account for case complexity) were not significantly related to adverse events in any of their study sites.

Schilling *et al.* [11] analyzed the relationship of high hospital occupancy, increased nurse staffing levels, weekend admissions, and seasonal influenza with predicted probability of death versus actual number of deaths. The study found that each of the factors had a statistically significant association with in-hospital mortality. Of the four factors, high hospital occupancy, had the third greatest influence on patient mortality leading to an increase in 0.24% points of actual death versus predicted death (95% CI 0.06–0.43) [11]. Because it is difficult to ascertain when the patient's illness ultimately becomes fatal, Schilling *et al.* looked at hospital occupancy on the day of admission. It may have been several days after admission, however, with a different level of hospital occupancy, that the patient became fatally ill. A better understanding of the consequences of high hospital occupancy on the occurrence of all severe adverse events (not just mortality) could help inform capacity management policies.

Understanding the probability of severe adverse events within the inpatient population as a function of hospital occupancy enables the development of appropriate resources and interventions to minimize these adverse events. By increasing knowledge within this field, it is hoped that hospitals can improve the management of hospital occupancy to benefit patient outcomes.

In this study, it was desired to apply regression modeling to examine the effect of occupancy on severe adverse events

Manuscript received January 7, 2013; revised April 12, 2013; accepted April 27, 2013. Date of publication May 7, 2013; date of current version December 31, 2013.

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Digital Object Identifier 10.1109/JBHI.2013.2262053

using a hospital inpatient cohort. Severe adverse events reported in a major accredited teaching hospital cross-matched to bed occupancy across a one-year time period were analyzed using logistic and multinomial regression models. This resulted in derivations of the probabilities of the occurrence of such events as a function of hospital occupancy.

II. Method

A. Study Site

This study was part of a larger project exploring the relationship between daily hospital occupancy rates and the occurrence of all reported adverse events from an inpatient population within an Australian public hospital. It was undertaken in South Australia at the Royal Adelaide Hospital—the state's largest teaching hospital with a capacity of approximately 650 acute care beds and 65 000 emergency presentations per year. Information relating to adverse events and occupancy was collected from hospital information systems for the year July 2009–June 2010 and analyzed on a daily basis. Occupancy was defined as the number of patients occupying inpatient beds at midnight compared with the budgeted fixed total hospital bed base.

B. Adverse Event Data

Clinical staff at the study site can report an adverse event using:

1) an incident report form;
2) directly online using a computer software program—the advanced incident management system (AIMS);
3) a 24-h contact center staffed by nurses.

These reports are then entered into AIMS and reviewed by the management of the health service. All incidents are assessed against a safety assessment code or SAC, which allocates a numeric score to the incident which guides the organization in appropriate management and action [12].

The SAC matrix categorizes incidents according to four levels based on consequence/severity and likelihood/probability. SAC1 incidents are adverse events that result in extreme or major harm to patients. Sentinel events are automatically grouped in this highest acuity level (SAC1) regardless of the outcome to the patient. Events categorized as SAC1 must be investigated by means of a root cause analysis (see Table I for examples of each of the four SAC levels).

The focus of the analysis was on severe (SAC1 and SAC2) adverse events due to their link with patient outcomes.

C. Probability Modeling

It was desired to determine the probabilities of severe adverse events occurring as a function of occupancy. The probability of an adverse event occurring was determined by collapsing daily counts to a binary outcome representing whether an event occurred or not, and using logistic regression to quantify the relationship with occupancy—see Section III-B. The probabilities of specific counts of severe events occurring per day (zero, one, two, etc. events/day) were then determined using multinomial logistic regression—see Section III-C.

TABLE I
Adverse Event Severity

SAC Level	Example	Action
SAC1 Extreme risk	A fall resulting in a fracture	Immediate action required - a Root Cause Analysis investigation must be commenced and Incident Brief forwarded to the Department of Health
SAC2 High risk	A patient receiving an overdose of medication, and needing treatment or a longer stay in hospital to correct the effects	Senior management attention needed - Notification to the Department of Health
SAC3 Moderate risk	The early formation of a pressure area	Management responsibility must be specified e.g. aggregate data then undertake practice improvement project.
SAC4 Low risk	Routine observations are missed or medications not given, but there are no ill effects to the patient	Manage by routine procedures - aggregate data then undertake practice improvement project.

Note: SAC=Safety Assessment Code; shaded severity levels indicate focus of analysis.

III. Results

A. Occupancy and Adverse Event Data

The median bed occupancy (midnight census) across the analysis period was 97.1% (IQR: 93.8–100.2%), and was significantly higher ($p < 0.001$) on weekdays (median 98.0%, IQR 95.2–100.9%) compared to weekends (median 94.7%, IQR 91.0–97.2%).

Out of 2611 reported adverse events, 20 (1%) were coded as SAC1 events (most severe) and 94 (4%) as SAC2 events. Across the 12 month study period, 45% ($n = 51$) of severe adverse events were related to clinical management, 43% ($n = 49$) were related to falls and 12% ($n = 14$) were related to medication. Fig. 1 shows that at most there were three SAC1 [see Fig. 1(a)] and SAC2 [see Fig. 1(b)] adverse events reported each day.

Half of the SAC1 events occurred above an occupancy level of 99% and half of the SAC2 events occurred above an occupancy level of 98%. This is noteworthy considering that median hospital occupancy across the whole year was 97%. One capacity management action arising from these observations may be to use the results to set appropriate thresholds based on historic patterns.

B. Probability of at Least One Severe Event Per Day

The effect of occupancy on the probability of at least one severe incident is shown in Fig. 2. The data circles indicate historical daily counts collapsed to binary outcomes (representing event occurrence or not) and the probability as a function of occupancy is given by the fitted curve.

The probability P of at least one severe event per day is

$$\log(P/(1-P)) = -5.49 + 4.55X, \text{where } X = \text{occupancy}. \tag{1}$$

$$\text{Written another way: } P = \frac{1}{1+e^{-5.49+4.55X}}. \tag{2}$$

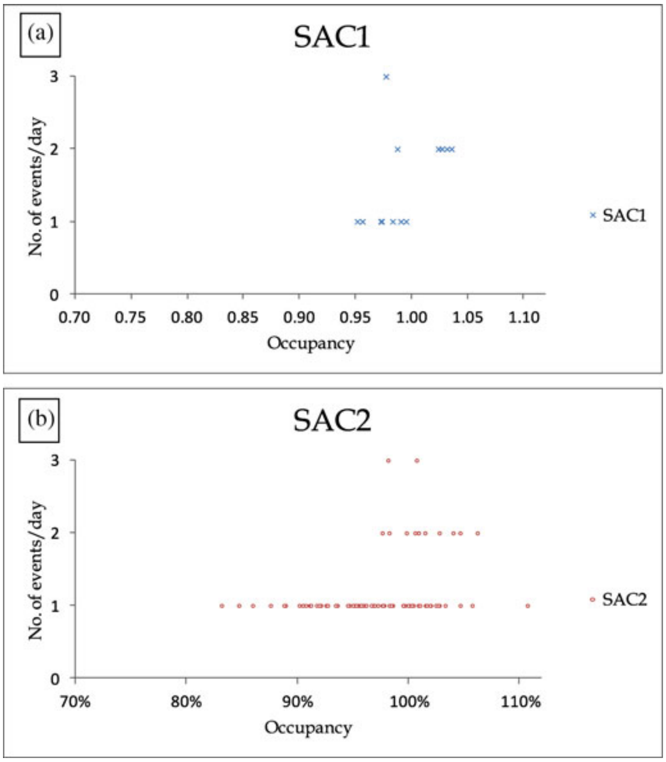

Fig. 1. Reported severe adverse events as a function of bed occupancy. SAC1 events (box A) are most severe and include sentinel events.

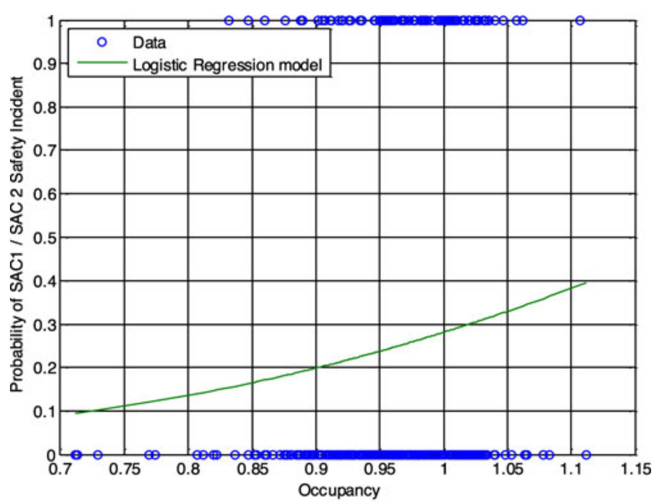

Fig. 2. Probability of at least one severe (SAC1/SAC2) event/day.

The positive regression coefficient (4.55) means that the occupancy explanatory variable increases the probability of a safety incident occurring. The modeling determined that for a 1% increase in occupancy, the odds of at least one severe (SAC1 or SAC2) event occurring increases by a factor of 1.05 (95% CI: 1.00–1.10). Fig. 3 includes 95% confidence bounds for the predicted values.

From Fig. 3, it can be seen that at 80% occupancy, there is around 15% probability of *at least one* severe adverse event, which increases to 20% probability at 90% occupancy, and around 28% probability at 100% occupancy.

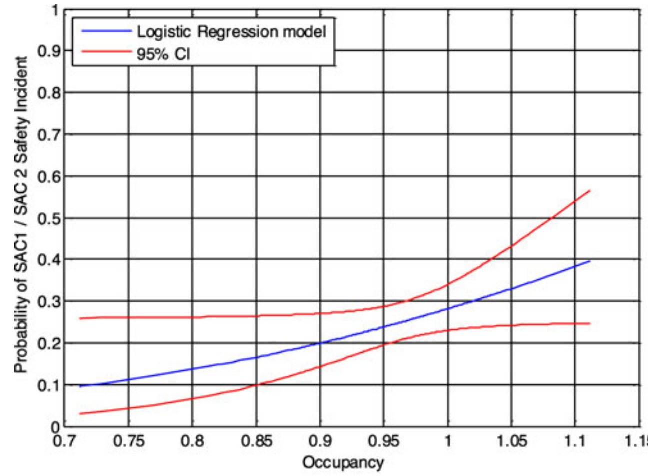

Fig. 3. Probability of at least one severe event/day with 95% CI.

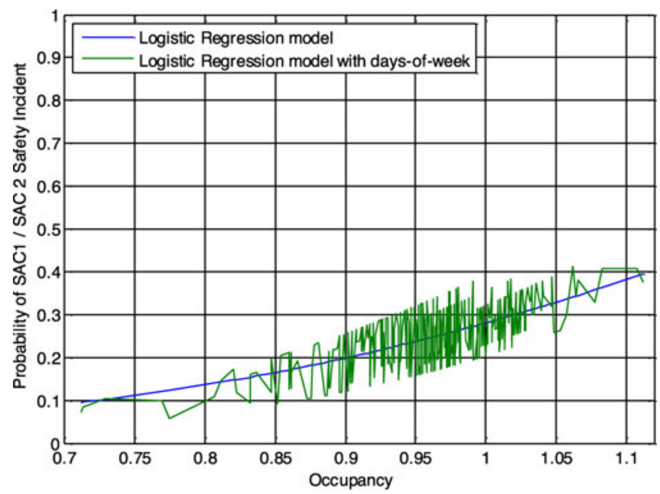

Fig. 4. Probability of at least one severe event/day as a function of occupancy and day-of-the-week.

One measure of model fit is the significance of the overall model. This test determines whether the model with occupancy as a predictor fits significantly better than a model with just an intercept (i.e., a null model). The aforementioned model as a whole fits significantly better than an empty model (likelihood ratio test: distributed chi-squared value $\chi^2 = 4.1$, with one degree of freedom, and associated p-value $= 0.04$).

Including days of the week as individual predictor variables improves the fit significantly ($\chi^2 = 5.2$, one-DOF $p = 0.02$). The model (see Fig. 4) then becomes:

$$\log(P/(1-P)) = -7.79 + 6.28X + 0.15W \qquad (3)$$

where $X =$ occupancy ($1 = 100\%$), and $W =$ day of the week (Sunday $= 1$, Saturday $= 7$).

C. *Probability of Zero, One, Two, or Three Severe Events/Day*

Multinomial logistic regression was used to determine the effect of occupancy on the probability of the counts of severe events occurring per day, i.e., the probability of zero, one, two, or three severe events occurring each day.

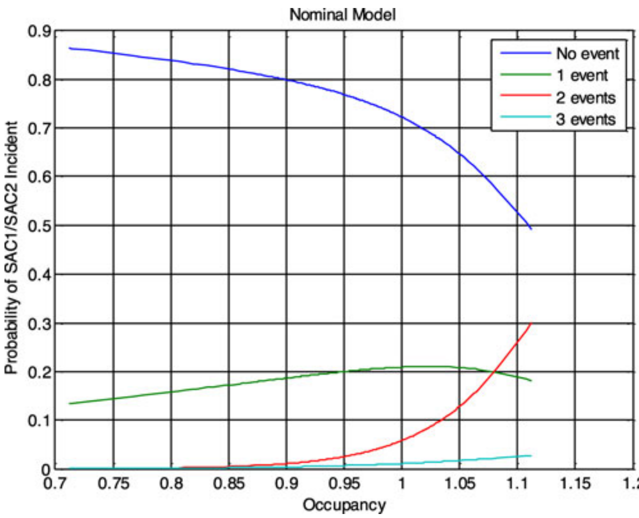

Fig. 5. Probabilities of zero, one, two or three severe adverse events using "nominal"-type multinomial logistic regression.

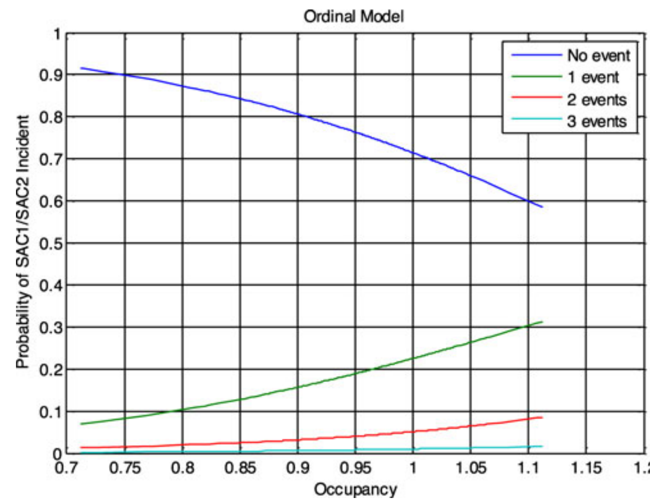

Fig. 6. Probabilities of zero, one, two, or three severe adverse events using "ordinal"-type multinomial logistic regression.

Two model types were compared:

1) "nominal" type, where it was assumed there is no ordering to the categories of daily event counts;
2) "ordinal" type, where there is actually an order to the categories of daily event counts.

Fig. 5 shows a "nominal" model, where it is assumed there is no ordering to the categories:

The model intercepts and coefficient terms describe the relationship between ratios of probabilities:

$$\log(P_{(1\,\text{event})}/P_{(\text{no events})}) = -3.39 + 2.15^{*}\text{Occupancy} \quad (4)$$

$$\log(P_{(2\,\text{events})}/P_{(\text{no events})}) = -20.70 + 18.17^{*}\text{Occupancy} \quad (5)$$

$$\log(P_{(3\,\text{events})}/P_{(\text{no events})}) = -15.77 + 11.54^{*}\text{Occupancy}. \quad (6)$$

For a one unit change in the variable occupancy, the log of the ratio of the two probabilities, $P_{(1\,\text{event})}/P_{(\text{no events})}$, will be increased by 2.15, the log of the ratio of the two probabilities $P_{(2\,\text{events})}/P_{(\text{no events})}$ will be increased by 18.17, etc. Therefore, we can say that, the higher the occupancy level, the more chance of adverse events (one, two or three events per day) compared to no events per day.

If we consider 1% occupancy intervals, the log of the ratios of $P_{(1\,\text{event})}$ to $P_{(\text{no events})}$ increases by 2.15/100 or 0.0215 for every 1% increase in occupancy.

The ratio of the probability of one outcome category over the probability of the reference category is often referred to as relative risk. So another way of interpreting the regression results is in terms of relative risk. We can say that for a 1% increase in occupancy, we expect the relative risk of:

1) SAC1/SAC2 adverse event over no adverse events to increase by $\exp(0.0215) = 1.02$;
2) SAC1/SAC2 adverse events over no adverse events to increase by $\exp(0.1818) = 1.20$;
3) SAC1/SAC2 adverse events over no adverse events to increase by $\exp(0.1154) = 1.12$.

So, we can say that the relative risk is higher for higher occupancy. The actual probabilities shown on the curves in Fig. 5 can be determined based on the knowledge that probabilities of all states have to sum to unity. That is

$$P_{(\text{no events})} + P_{(1\,\text{event})} + P_{(2\,\text{events})} + P_{(3\,\text{events})} = 1 \quad (7)$$

where

$$P_{(1\,\text{event})} = \exp(-3.39 + 2.15^{*}\text{Occupancy})^{*}P_{(\text{no events})} \quad (8)$$

$$P_{(2\,\text{events})} = \exp(-20.70 + 18.17^{*}\text{Occupancy})^{*}P_{(\text{no events})} \quad (9)$$

$$P_{(3\text{events})} = \exp(-15.77 + 11.54^{*}\text{Occupancy})^{*}P_{(\text{no events})}. \quad (10)$$

Fig. 6 shows probabilities derived using an "ordinal" type of multinomial logistic regression model. Ordinal models do not include interaction between the multinomial categories and the coefficients. That is, we fit a model with a common set of coefficients for the occupancy predictor variable, across all multinomial categories (*parallel regression*).

The coefficients for the ordered logit model ($\alpha_1 = 6.02$, $\alpha_2 = 7.85$, $\alpha_3 = 9.75$, $\beta = -5.11$) are used to define the following probability relationships:

$$\log \frac{P_0}{1 - P_0} = \alpha_1 + \beta X \quad (11)$$

where X = hospital occupancy and P_0 = the probability of no severe events/day. Rearranging (11) gives

$$P_0 = \frac{1}{1 + e^{-(\alpha_1 + \beta X)}}. \quad (12)$$

The probabilities of other states can be found by expanding the logit terms as follows:

$$\log \frac{P_0 + P_1}{1 - P_0 - P_1} = \alpha_2 + \beta X \tag{13}$$

$$\log \frac{P_0 + P_1 + P_2}{1 - P_0 - P_1 - P_2} = \alpha_3 + \beta X, \text{ and} \tag{14}$$

$$P_0 + P_1 + P_2 + P_3 = 1. \tag{15}$$

For a one unit increase in occupancy, we would expect a 5.11 change in the expected log value of the probability of different severe adverse event daily numbers. Since occupancy is modeled as $1 = 100\%$, for every 1% occupancy increment, we would expect a $5.11/100 = 0.05$ decrease on the log scale. For a 1% increase in occupancy, we expect the relative risk of:

1) SAC1/SAC2 adverse event over no adverse events to increase by $\exp(5.11/100) = 1.05$.
2) SAC1/SAC2 adverse events over 1 adverse events to increase by $\exp(5.11/100) = 1.05$.
3) SAC1/SAC2 adverse events over 2 adverse events to increase by $\exp(5.11/100) = 1.05$.

For an increase of just 1% in hospital occupancy, the odds of moving to a higher number of severe adverse events reported daily is 1.05 (95% CI: 1.01–1.1).

When hospital occupancy increases from its low or first quartile (93.8%) to its high or third quartile (100.2%), the odds of moving from none to one or more severe adverse events, or from a level of one or more to higher numbers is multiplied by 1.39 (95% CI: 1.04–1.85).

Comparing the multinomial logistic regression methods ("nominal"-type versus "ordinal"-type), we find that the "common" increase in relative risks across all multinomial categories with the ordered logit model (1.05) lies between the varying relative risks obtained using "nominal"-type multinomial logistic regression (1.02–1.12). The proportional odds assumptions of using an "ordinal"-type model were tested and given that it could be argued that an ordering does exist between categories of daily event counts, and noting that the probability curves depicted in Fig. 6 appear reasonable, the ordered logit model seems appropriate.

The interpretation of this multinomial regression modeling is that as hospital occupancy increases, the probability of having no safety incidents decreases, while the probability of one or two or three incidents per day increases, although it remains low (below 50% chance).

At a hospital occupancy level of 80%, there is a 10% chance of *one* severe incident, increasing to 20% chance at 95% occupancy, and 30% chance at 110% occupancy. Fig. 7 includes 95% confidence intervals around predicted probabilities using the ordered logit model.

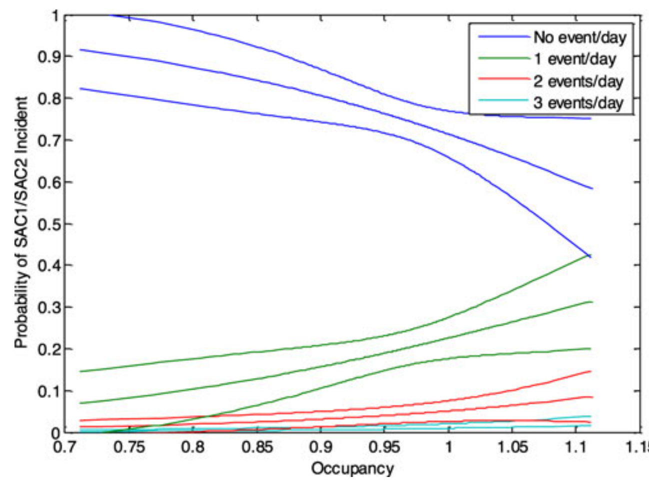

Fig. 7. Probabilities of varying daily counts of severe adverse events including 95% confidence intervals (ordered logit model).

IV. Discussion

This study has provided insight into understanding the relationship between hospital occupancy and adverse events within an inpatient population. The analysis covered two modeling approaches:

1) logistic regression (logit regression)—based on collapsing daily counts of adverse events to a binary outcome representing whether an event occurred or not; this determined that at a hospital occupancy level of 100%, there is a 28% chance of *at least one* severe event occurring;
2) multinomial logistic regression (multinomial logit)—allowing more than two discrete outcomes, which was used to predict the probabilities of the different possible outcomes (0, 1, 2, or 3 events per day); this determined that at a hospital occupancy level of 100%, there is a 22% chance of *one* severe event occurring.

All modeling resulted in positive regression coefficients, indicating that as hospital occupancy increases, there is a higher probability of a severe adverse event occurring.

The work demonstrates an application of multinomial logistic regression using the statistical package "R" which has the advantages of being free and availability of a good user support base. It is noted that similar modeling can be performed using other statistical packages, such as SAS, SPSS, Stata, and MPlus, which were not investigated in this study.

The management action arising from such analysis is to use the findings to inform capacity management policy within hospitals. It has been stated [13] that although most adverse events are preventable, some adverse events cannot be predicted—for example, drug reactions in patients who had not taken the drugs previously, or postoperative myocardial infarctions in patients without previous evidence of heart disease. A typical hospitalization may involve many encounters between a patient and doctors, nurses, hospital staff, and equipment, and unexpected results or errors can occur with each encounter, perhaps causing an adverse event. A challenge for hospital management is determining a capacity level corresponding to an "acceptable" number of adverse events—and identify the corresponding occupancy level from the probability plots.

The limitation of this analysis is that only one hospital and one year of data were used to generate the results. Midnight bed occupancy was used as opposed to hourly occupancy, and hourly occupancy may be considered more appropriate for capacity management as it captures the "churn" that occurs throughout a day [14]. Information was not available regarding age, comorbidity data, or length of stay information for the affected patients nor the specialty area within the hospital, and these effects may influence these results. Finally, adverse event data were dependent upon "self-report" and thus potentially biased. A reporting culture is crucial in the detection and management of adverse events and near misses, and the study site has sought to determine staff barriers to incident reporting and developed interventions to overcome identified reporting barriers which are in active use [12].

Appropriate hospital capacity management is one of the many solutions to help reduce adverse events. Analysis against other interventions to reduce adverse events is outside the scope of this study, but such interventions can include scientific advances (e.g., developing less hazardous chemotherapeutic agents) [13], education and standards for practice [13], increased health-care worker hand-hygiene compliance [15], cohorting of patients (restricting contact with patients to an assigned health-care worker) [15], automatic "fail-safe" systems such as computerized systems that makes it impossible to order or dispense a drug to a patient with a known sensitivity [16], computerized surveillance using natural language processing to mine electronic medical records [17], falls risk assessment and management programs [18], and developing better mechanisms of identifying negligent behavior.

Awareness of hospital capacity management as an intervention is required and this study informs the debate and provides evidence that safety within inpatient wards of hospitals is affected as hospital beds are filled to capacity.

V. Conclusion

Hospital managers balance a range of competing priorities on a daily basis including pressures to optimize bed utilization. The evidence generated through regression analysis has quantified the probabilities of adverse events as a function of occupancy and links severe adverse events with high occupancy levels within a hospital. Any effort to reduce inpatient occupancy is thus crucial from a patient safety perspective.

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