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Mortality among high-risk patients admitted with septic shock to U.S. teaching hospitals in July: Does the 'July Effect' exist?

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ABSTRACT

Background: The 'July effect' is a phenomenon of inferior delivery of care at teaching hospitals during July because of relative inexperience of new physicians.
Objective: To study the difference in mortality among septic shock patients during July and another month.
Methods: Using the U.S. Nationwide Inpatient Sample, we estimated the difference in mortality among septic shock patients admitted during May and July from 2003 to 2011.
Results: 117,593 and 121,004 patients with septic shock were admitted to non-teaching and teaching hospitals, respectively, in May and July. High-risk patients had similar mortality rates in non-teaching hospitals and teaching hospitals. Mortality rates were higher in teaching versus non-teaching hospitals in high-risk patients both in May and July. Overall, mortality rates were higher in teaching versus non-teaching hospitals both in May and July.
Conclusion: Similar trends in mortality are observed in both settings in May and July and no "July effect" was observed.

Introduction

The 'July effect' is described as a period of inferior care delivery at teaching hospitals which coincides with transition of medical students into the active healthcare force as interns, the most junior and frontline healthcare providers. This is also the time when graduating residents would join the workforce as junior attendings or fellows. There is much debate about the validity of this phenomenon and a better understanding could play an important role in preventing as many as 440,000 deaths every year attributed to preventable medical errors, the third leading cause of death in the United States.[1] It could also have a significant impact on cost of care in teaching hospitals, which is thought to be 18% higher than non-teaching hospitals, with it being highest early in the academic year.[2] The time of transition of patient care responsibilities to less-experienced physicians has been a topic of interest not only in the US but also in other developed healthcare systems.[3]

Prior studies of estimated July effects have shown mixed results and most of them do not examine whether the July effect varies according to the predicted risk of in-patient mortality.[4] Patients with a low predicted risk of in-patient mortality may not be affected by inexperienced physicians as much as patients with a high risk of in-patient mortality.

The population at the highest predicted risk of in-patient mortality is that admitted to the Intensive Care Unit (ICU). Studies looking at the 'July effect' in this population have also shown varied results likely because of including ICU patients as a homogenous group and not categorizing them based on their diagnoses or setting such as surgical, trauma or medical ICU.[5] A disease-specific approach to study mortality trends, such that done by Jena et al in acute myocardial infarction patients,[4] would provide the most bias-free understanding of the July effect. Thus, the objective of our study was to compare mortality rates of patients admitted with

Abbreviations: AHRQ, Agency for Healthcare Research Quality; CCI, Charlson Comorbidity Index; HCUP, Healthcare Utilization Project; ICD-9, International Classification of Disease-9; ICU, Intensive Care Unit; LOS, length of stay; NIS, Nationwide Inpatient Sample; SAS, Statistical Analysis Software; SD, standard deviation.

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septic shock between May and July in teaching and non-teaching ICUs.

Methods

Data source

We quarried the Nationwide Inpatient Sample (NIS) of Healthcare Utilization Project (HCUP) to identify patients with septic shock. This database includes information about hospitalization such as age, sex, race, comorbid illnesses, length of stay (LOS), total charges, teaching status, hospital location, and hospital bed size. The diagnoses are coded using the International Classification of Disease, ninth revision (ICD-9). Teaching hospitals were defined as those with more than 0.6 residents per bed, while non-teaching hospitals were defined as all others.

Study sample

We identified patients admitted with septic shock from 2003 to 2011 using the appropriate ICD-9 code. We studied hospitalizations over 12 months to evaluate trends in mortality and specifically quantify the difference between May and July. We also analyzed mortality difference between teaching and non-teaching hospitals throughout the year.

Outcome variable

The primary outcome variable was all-cause in-patient mortality. Our primary hypothesis was that patients admitted to teaching hospitals during July experience higher mortality rates compared to those admitted during May. Relative inexperience of residents during the month of July may adversely affect outcomes of patients admitted with septic shock when early recognition and treatment is necessary.

Statistical analysis

We analyzed the baseline characteristics of admitted patients at teaching and non-teaching hospitals in the months of May and July. Categorical variables were displayed as a percentage and continuous variables were displayed as mean $\pm$ standard deviation (SD). A Chi square analysis was used to show a difference in categorical variables and *T*-test analysis for continuous variables.

NIS database is a complex survey sample design which includes stratification, cluster and weights. Surveylogistic model was used in Statistical Analysis Software (SAS for windows) for this sample to evaluate maximum likelihood, variance of regression and odds ratios. Multivariate models were created to evaluate odds ratio for mortality in teaching versus non-teaching hospitals during each particular month. Outcomes of the multivariate model for May and July were compared to look for the "July effect".

The sample was stratified into high-risk and low-risk categories using the Charlson Comorbidity Index (CCI). A CCI of greater than or equal to 2 was defined as high-risk whereas a CCI of less than 2 was defined as low-risk. Separate multivariate models were created for each group for further risk stratification.

Results

A total of 117,593 patients with septic shock presented to non-teaching hospitals and 121,004 to teaching hospitals in the months of May and July between 2003 and 2011. There was no statistical difference in the total number of admissions to teaching and non-teaching hospitals between the two months.

Demographics

There were more females admitted to non-teaching hospitals in both months with no significant difference between the months, while more males were admitted to teaching hospitals. There was no difference in the distribution of age of patients in both months in either hospital setting, with 65–79 year old patients sharing the highest percentage in both hospitals in both months (Table 1). The Agency for Healthcare Research Quality (AHRQ) comorbidity measures were also well-matched in both groups (Table 2). The patients presenting to non-teaching hospitals were more likely to have Medicare/Medicaid as their primary insurance. The urgency of the admission (elective versus emergent) was well-matched in both months in both settings however it did not meet statistical significance (Tables 3 and 4).

Primary outcome measure

High risk patients

High-risk patients (Charlson score > 2) had similar mortality rates in non-teaching hospitals in both months (40.7% in May and 38.2% in July), which was also true for teaching hospitals (45.5% in May and 44.3% in July). Interestingly, higher mortality rates were observed in teaching versus non-teaching hospitals in high-risk patients, both in May (45.4% vs. 40.7% $p \leq 0.0001$) and July (44.3% vs. 39.8% $p \leq 0.0001$).

Low risk patients

Among low-risk patients (Charlson score < 2), similar mortality rates were observed in both months in non-teaching hospitals (May 34% vs. July 32.5%) and teaching hospitals (May 35.7% vs. July 35.5%). No significant difference in mortality rates were observed in teaching versus non-teaching hospitals in May (35.2% vs. 34%, $p = 0.12$) while higher mortality rates were observed in teaching versus non-teaching hospitals in July (35.4% vs. 32.4%, $p = 0.006$) (Fig. 1).

Overall mortality rates were significantly higher in teaching versus non-teaching hospitals both in May (41.4% vs. 37.8%, $p \leq 0.001$) and July (40.6% vs. 36.6%, $p \leq 0.001$), with a similar trend seen throughout the year. There was a significantly higher likelihood of mortality in teaching versus non-teaching hospitals throughout the year in both high and low-risk patients, but the effect of teaching status on mortality was not significant.

Table 1
Baseline demographics.

	Non-teaching hospital			Teaching hospital		
Month	May	July	*p*-Value	May	July	*p*-Value
Demographic variable						
Total patients	58,715	58,882		60,093	60,916	
Patient level variables						
Age (%)			0.1244			0.536
18–34	2.9008	3.4425		4.8459	5.1284	
35–49	8.4156	8.7953		11.3961	11.7437	
50–64	24.7929	24.5593		28.7168	28.2138	
65–79	35.4578	34.9187		32.2307	32.6189	
≥80	28.433	28.2844		22.8106	22.2951	
Sex (%)			0.6538			0.4361
Male	49.3492	49.0645		51.1774	51.6748	
Female	50.6508	50.9355		48.8226	48.3252	
Race			0.3982			0.1525
White	71.6136	70.7101		65.6	64.4315	
Black/Hispanic	21.4606	22.2327		26.9213	28.1643	
Other	6.9258	7.0572		7.4787	7.4042	