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Electronic Medical Records and the Efficiency of Hospital Emergency Departments

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Abstract

This study examined the relationship between electronic medical records (EMR) sophistication and the efficiency of U.S. hospital emergency departments (EDs). Using data from the 2006 National Hospital Ambulatory Medical Care Survey, survey-weighted ordinary least squares regressions were used to estimate the association of EMR sophistication with ED throughput and probability a patient left without treatment. Instrumental variables were used to test for the presence of endogeneity and reverse causality. Greater EMR sophistication had a mixed association with ED efficiency. Relative to EDs with minimal or no EMR, fully functional EMR was associated with 22.4% lower ED length of stay and 13.1% lower diagnosis/treatment time. However, the relationships varied by patient acuity level and diagnostic services provided. Surprisingly, EDs with basic EMR were not more efficient on average, and basic EMR had a nonlinear relationship with efficiency that varied with the number of EMR functions used.

Keywords

efficiency, emergency department, information technology

Introduction

Hospital emergency departments (EDs) play a major role in the U.S. health care system, serving millions of patients each year. From 1996 to 2006, the number of ED visits per year increased by 32%, while the supply of EDs and inpatient beds declined

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(Pitts, Nishka, Xu, & Burt, 2008). Amidst rising pressures, many EDs are overburdened and crowding remains a national concern (U.S. General Accountability Office, 2003). Crowding can impede patient flow and can lead to ambulance diversions, patients leaving without treatment, boarding of patients waiting to be admitted, and waits to see a physician that exceed recommended times (U.S. General Accountability Office, 2009). Among the negative consequences of crowding are increased transport times, prolonged pain and suffering (Pines & Hollander, 2008), delays in treatment (Pines et al., 2007), and other adverse clinical outcomes (Bernstein et al., 2009).

While the reasons for crowding are complex and varied, various strategies have been proposed to enhance operational efficiency (Hoot & Aronsky, 2008). One strategy is health information technology (IT), which can improve access to patient information and support clinical decision making. In general, health IT has been projected to lower costs, improve efficiency and patient safety, and enhance quality of care (Blumenthal et al., 2008; Hillestad et al., 2005). In the ED setting, health IT has been proposed as a tool to improve the timely and efficient provision of emergency care (Institute of Medicine [IOM], 2006). One of the promising health IT applications is electronic medical records (EMR), which automates the paper-based patient chart and can improve clinical decisions.

Despite strong interest in health IT by policy makers (Clancy, 2007a, 2007b) and practitioners (Bullard, Emond, Graham, Ho, & Holroyd, 2007), adoption of advanced EMR functionality has been slow in inpatient (Jha et al., 2009) and ED settings (Pallin, Sullivan, Auerbach, & Camargo, in press). While evidence implies some benefits, little research has examined the impact of EMR systems in community hospitals (Chaudhry et al., 2006).

New Contribution

In this study, we examined the relationship between EMR sophistication and the efficiency of hospital-based EDs using a nationally-representative data set. Our study differed from others in the literature in several ways. First, most prior work has focused on specific EMR applications or treated EMR as a binary indicator for the presence of any EMR. Here, we focused on the level of EMR sophistication using classifications developed by a consensus panel of experts. Second, we decomposed the effects on length of stay (LOS) into the two primary phases of throughput (wait time vs. treatment time) and explored variation by visit characteristics. To our knowledge, this was the first large-scale study to estimate the relationship between EMR sophistication and ED efficiency using nationally representative data. The findings from this study provide important evidence on the value of health IT in emergency care.

Conceptual Framework

To understand the association of EMR sophistication with ED efficiency, we developed a conceptual model based on the Input–Throughput–Output model of ED

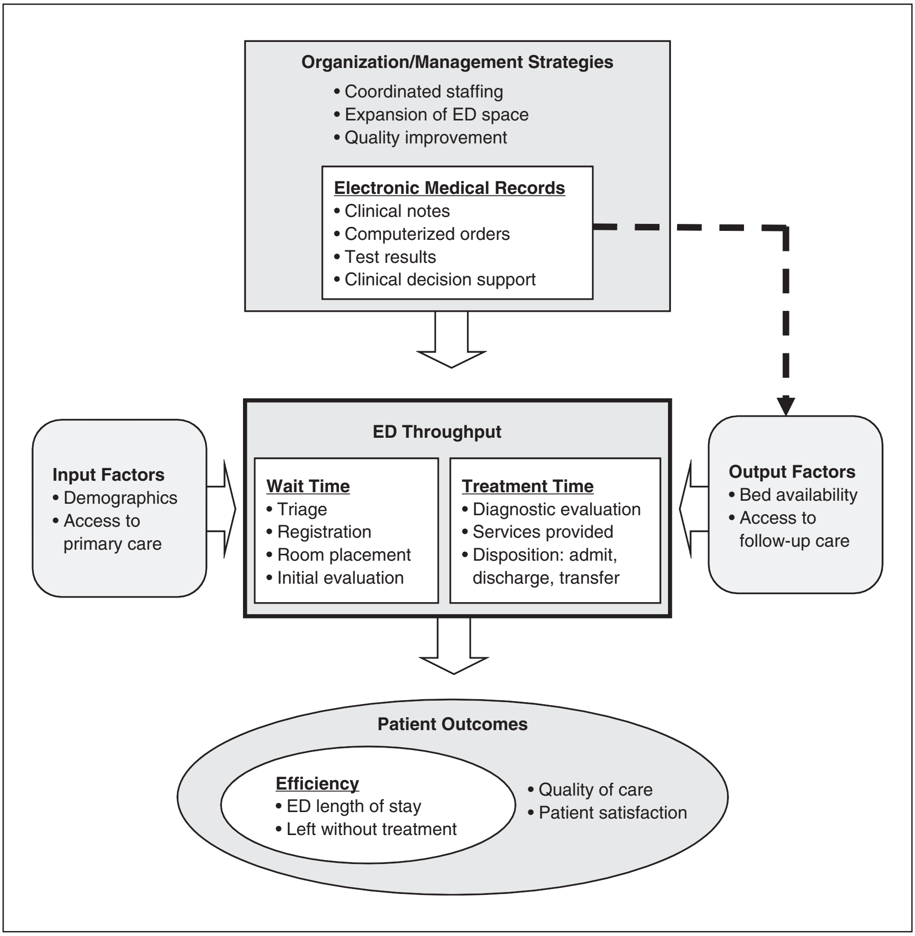

Figure 1. Conceptual Model of Electronic Medical Records (EMR) and Emergency Department (ED) Throughput

crowding (Asplin et al., 2003). The Asplin model conceptualizes that patient flow is determined by three interdependent components: input factors, output factors, and ED throughput. "Input factors" influence the demand for ED services, and "Output factors" affect the disposition time required for admission, discharge, or transfer. "ED throughput" is affected by input and output factors as well as organizational and management strategies, such as coordinated staffing, expansion of ED space, quality improvement, and IT use.[1] In our conceptualization (Figure 1), EMR is one example of an organizational/management strategy that affects ED throughput, as measured by LOS.

Prior research has examined the relative impact of input versus output factors on ED efficiency (Asaro, Lewis, & Boxerman, 2007a, 2007b; Bickell, Hwang, Anderson, Rojas, & Barsky, 2008; Gardner, Sarkar, Maselli, & Gonzales, 2007). While some organizational and management strategies may influence efficiency (Moskop, Sklar, Geiderman, Schears, & Bookman, 2009), few large-scale studies have examined the impacts of IT or EMR on ED efficiency.

Inpatient EMR might affect ED efficiency as a component of an Emergency Department Information System (EDIS) or as part of a hospital-wide integrated system.[2] In theory, EMR can improve hospital efficiency by providing access to patient information, automating manual tasks, standardizing orders and documentation, improving patient tracking, and facilitating communication among a multidisciplinary team (IOM, 2006).

The impact of EMR might vary by the level of EMR sophistication. EMR might provide real-time and remote access to an electronic patient chart, containing problem lists and medication history (Feied et al., 2004). Clinical documentation systems can improve the speed of charting through templates and flow sheets that guide providers through standardized care plans (Davidson, Zwemer, Nathanson, Sable, & Khan, 2004; B. Taylor et al., 2008). Computerized physician order entry (CPOE) can reduce the need for pharmacist clarification (Bizovi et al., 2002), and standardized order sets can speed the ordering of routine diagnostic services. More advanced EMR systems can capture and share physician notes (Hripcsak, Sengupta, Wilcox, & Green, 2007) and include clinical decision support (CDS) systems, which can reduce uncertainty and enhance clinical decision making (Handler et al., 2004; Holroyd, Bullard, Graham, & Rowe, 2007).

In the ED, EMR may facilitate patient tracking by providing multiple caregivers with simultaneous access to the electronic chart and by integration with a computerized whiteboard (Aronsky, Ones, Lanaghan, & Slonvis, 2008). Some EMR functions may be targeted to arrival processes and have a direct impact on wait time. Collection and storage of patient demographic information can speed registration by eliminating duplicate data entry and errors by clerical staff (Hakimzada, Green, Sayan, Zhang, & Patel, 2008). Computer-assisted triage protocols and automated triage systems can speed referral of nonurgent patients to appropriate levels of medical care and facilitate advance ordering of diagnostic tests (Dong et al., 2005).

Other EMR functions can affect diagnosis and treatment time. Electronic ordering and online retrieval of results can improve laboratory and radiology turnaround times, which have been projected to enhance ED throughput (Storrow et al., 2008). Digital radiography with a Picture Archiving and Communication System (PACS) can make electronic images available in the ED (White et al., 2004). Some EMR systems include discharge planning and communication systems with automatic notification for bed requests and room turnover, referrals with follow-up notes, and the ability to produce electronic discharge instruction sheets and printed prescriptions (IOM, 2006).

In addition to internal benefits, an EMR system may help coordinate care beyond the ED through integration with a hospital-wide information system or interoperability with emergency medical services (Reddy et al., 2009) and health information exchanges (Shapiro et al., 2006).

EMR might also indirectly affect ED efficiency. EMR use in medical surgical units can reduce inpatient LOS (Mekhjian, Kumar, Kuehn, Bentley, & Teater, 2002), which might improve bed availability for ED patients. EMR linked with a clinical data repository can provide performance measures to be used retrospectively for process improvement (Husk & Waxman, 2004).

Despite potential benefits, EMR may have negative and unintended consequences. A poorly designed user interface with fragmented screens and multiple sign-ons can increase computer time and lead to user dissatisfaction (Likourezos et al., 2004). CPOE and CDS may slow providers and create their own type of errors, which can further delay care by requiring rework (Koppel et al., 2005). EMR implementation can be a complex and difficult task; partial implementation and/or inadequate training can lead to clinician resistance and failure (Handel & Hackman, in press; T. B. Taylor, 2004; Yamamoto & Khan, 2006).

Prior studies of EMR and provider time efficiency in inpatient and outpatient settings have been mixed (Poissant, Pereira, Tamblyn, & Kawasumi, 2005). Most prior work has focused on specific EMR functions in self-developed systems at pioneering institutions (Chaudhry et al., 2006). Across types of care, little evidence documents the benefits of EMR from commercial systems used in community settings. In the ED setting, the net impact of advanced EMR functionality on efficiency remains an empirical question.

Method

Data Source

The study used the 2006 National Hospital Ambulatory Medical Care Survey (NHAMCS). The NHAMCS is a national probability sample survey of visits to U.S. hospital EDs conducted by the National Center for Health Statistics, Centers for Disease Control and Prevention.

The basic sampling unit was the patient visit or encounter, and visits were systematically selected over a randomly assigned 4-week reporting period. ED staff completed a patient record form (PRF), which included information on patient and visit characteristics. A separate hospital induction interview collected data on hospital characteristics, which included EMR use. The survey included weights to allow reporting of nationally-representative estimates.

The data set included 35,849 patient record forms from 364 hospital-based EDs. This sample represented a national weighted population of 119.2 million visits to 4,654 EDs.

EMR Sophistication

The main variable of interest is whether the ED used an EMR system. The NHAMCS asks “Does your ED use electronic medical records (not including billing records)?” The survey also asked whether the ED’s EMR system included any of 13 EMR functions (Table 1). Nonresponse and survey responses of “unknown” and “turned off” were included as not having the EMR system or function.

Table 1. Electronic Medical Records (EMR) Use in U.S. Hospital Emergency Departments, 2006

		EMR Sophistication		
	All EDs	Minimal or No EMR[a]	Basic EMR[b]	Fully Functional EMR[c]
Emergency department (ED) uses EMR system, %	46.2	87.5	10.8	1.7
Functions included in EMR system,[d] %				
Minimum set of EMR functions				
Patient demographic information	95.2	36.0	100.0	100.0
Laboratory results	89.3	32.8	100.0	100.0
Computerized orders for tests	82.2	29.1	100.0	100.0
Imaging results	73.4	24.4	100.0	100.0
Clinical notes	63.8	19.4	100.0	100.0
Computerized orders for prescriptions	49.0	11.6	100.0	100.0
Advanced EMR functions				
Out of range levels highlighted	66.2	24.4	69.5	100.0
Test orders sent electronically	60.3	20.1	79.8	100.0
Medical history and follow-up notes	49.7	14.3	80.8	100.0
Electronic images returned	42.1	12.4	63.5	100.0
Warnings of drug interactions and contraindications provided	33.0	6.6	71.7	100.0
Reminders for guideline-based interventions and/or screening tests	31.8	9.6	42.3	100.0
Prescriptions sent electronically to pharmacy	15.2	3.8	18.4	100.0
Instrumental variables				
Public health reporting only	7.0	5.0	23.2	7.6
Both public health reporting and notifiable diseases sent electronically	4.7	1.9	20.2	51.9
EMR functions used,[e] #	7.51	2.45	10.26	13.0
N (EDs)	364	294	60	10
Population (EDs)	4,654	4,074	501	79
N (ED visits)	35,849	28,553	6,310	986
Population (ED visits; million)	119.2	95.9	20.5	2.8

Note: Estimates are weighted to be nationally representative.
a. Minimal/no EMR has *less than* the minimum set of EMR functions.
b. Basic EMR has *at least* the minimum set of EMR functions.
c. Fully functional EMR has the minimum set of EMR functions *in addition to* all advanced EMR functions.
d. Conditional on any use of EMR.
e. Excludes public health reporting and notifiable diseases sent electronically.

We used definitions developed by expert opinion to classify EMR sophistication into three mutually exclusive categories: minimal/no EMR, basic EMR, and fully functional EMR (DesRoches et al., 2008). "Minimal/no EMR" was defined as having no EMR or an EMR system with *less than* a minimum set of EMR functions (patient demographic information, clinical notes, computerized orders for prescriptions, laboratory results, and imaging results), "basic EMR" as an EMR system that included *at least* the minimum set, and "fully functional EMR" as an EMR system that included the minimum set *in addition to* seven advanced EMR functions. The principal difference between basic and fully functional EMR systems is the presence of advanced functions for managing orders/results (i.e., electronic images returned) and CDS capabilities (i.e., warnings of drug interactions provided).

We were concerned about potential bias from endogeneity and reverse causality. Reverse causality might arise if more efficient hospitals were early adopters of EMR technology. While we controlled for some observable hospital characteristics, omitted variables correlated with ED efficiency and EMR sophistication might bias our results. We used instrumental variables (IV) to address potential endogeneity. For IVs, we created variables for whether the ED's EMR system included functions for public health reporting and notifiable diseases sent electronically (Table 1). Our identification strategy relied on state variation in electronic disease surveillance systems. The IT capabilities of public health agencies and their operational status varied widely across states (Dwyer, Foster, & Safranek, 2007). Furthermore, lack of uniform data standards for interoperability posed a major barrier to integration with commercial EMRs (Kukafka et al., 2007). While automated reporting of vital statistics and disease notification might reduce ED administrative burden, we believed retrospective reporting was plausibly unrelated to clinical care processes, except through its relationship with EMR sophistication. We performed Hausman tests and found almost no evidence of endogeneity.[3] The IVs were highly significant predictors of EMR sophistication (F statistic was 22.8), and overidentification tests confirmed the exogeneity of the IVs.[4]

ED Efficiency

We specified two aspects of ED efficiency: ED throughput and the probability that a patient left without treatment (LWOT).[5] We measured ED throughput by the LOS in minutes. We further decomposed LOS into the wait time to see a physician (wait time) versus diagnosis and treatment time (treatment time). Records with missing time information were excluded from the analysis.[6] Descriptive statistics on ED efficiency are reported in Table 2.

Patient and Visit Characteristics

We specified measures of patient characteristics, including age, sex, race/ethnicity, expected source of payment, and whether the patient resided in a nursing home or other institution.

Table 2. Descriptive Statistics of Emergency Department (ED) Throughput and Left Without Treatment

	N	*M*	*SD*
ED throughput, minutes			
ED length of stay			
All patients	32,510	200.3	208.1
Visit disposition			
Admitted to hospital	4,412	326.6	289.6
Discharged to home	27,486	178.0	180.4
Wait time to see a physician			
All patients	28,071	55.9	81.1
Patient acuity level/triage			
Immediate/emergent	4,994	34.7	59.9
Urgent/semiurgent	16,334	56.6	73.3
Nonurgent/no triage	6,743	70.1	107.3
Diagnosis and treatment time			
All patients	27,347	149.6	192.3
Diagnostic services provided			
No diagnostic services	5,454	70.9	120.8
Any diagnostic service, no imaging	9,553	141.5	207.2
Any imaging procedure	12,340	189.0	194.8
Left without treatment, percentage			
All patients	35,849	3.25	
Patient acuity level/triage			
Immediate/emergent	5,831	1.79	
Urgent/semiurgent	19,997	2.72	
Nonurgent/no triage	10,021	5.35	

Note: Estimates are weighted to be nationally representative.

We created measures of visit characteristics, including month of visit, day of week, patient acuity level/triage, diagnostic services provided, and psychiatric diagnosis. Following Gardner et al. (2007), we categorized patients into three mutually exclusive categories based on diagnostic services provided (blood tests, imaging procedures, other procedures). "No diagnostic services" was defined as patients receiving no diagnostic service; "any diagnostic service, no imaging" was defined as patients receiving any diagnostic service but no imaging procedure; and "any imaging procedure" was defined as patients receiving any imaging procedure. We identified patients with any psychiatric diagnosis based on whether any reported ICD-9 (International Statistical Classification of Related Health Problems) diagnosis codes were in the range 290 to 319.

Hospital and Area Characteristics

We created measures of hospital characteristics, including ownership, teaching status, critical care services, and hospital acuity mix. We identified teaching status based on whether residents/interns provided care to any patients during the sample period. We identified hospitals with a critical care unit based on whether any patients had been admitted to the CCU during the sample period. For measures of hospital volume and acuity mix,[7] we calculated the percentage of visits admitted to the hospital, percentage of visits with Immediate/Emergent acuity as a proxy for trauma level, and percentage of visits with Nonurgent/No triage acuity as a proxy for ED volume.

We also included area characteristics based on the patient's zip code of residence to control for geographic factors that might influence ED efficiency. Descriptive statistics for patient, visit, hospital and area characteristics are available on request from the author.

Survey-Weighted Regression Models

We employed survey-weighted ordinary least squares (OLS) to estimate the relationship between EMR sophistication and ED throughput. We applied a log transformation to the dependent variables for LOS, wait time, and treatment time.

We used survey-weighted probit regression to estimate the relationship between EMR sophistication and LWOT and survey-weighted ordered probit regression to examine the association of hospital and area characteristics with the level of EMR sophistication. All estimation was performed using Stata 10.1 statistical software.[8]

Analysis

For analyses of ED throughput, we focused on patients with visit disposition of admit, discharge, or transfer; we excluded patients who died or LWOT because of concerns about measurement error. We analyzed all patients and separately by visit disposition, patient acuity level/triage, and diagnostic services provided.

We reported marginal effects for EMR sophistication, relative to EDs with minimal/no EMR. To test whether the effects of EMR sophistication were incremental, we conducted postestimation tests of linear restrictions of the hypothesis that basic EMR = fully functional EMR. This allowed us to report whether greater levels of EMR sophistication had a dose–response relationship with ED efficiency.

Sensitivity Analysis

We tested the sensitivity of our results to the classification of EMR sophistication. We created a continuous measure of the level of EMR sophistication based on the number of EMR functions used. We allowed EMR to have a nonlinear relationship with efficiency by including the number of functions and the square of functions in our regression models. We generated predicted means from survey-weighted OLS regressions and stratified by the number of EMR functions. To test for significant differences, we performed analysis of variance contrasts relative to minimal/no EMR.[9]

Results

EMR Use in Hospital Emergency Departments

Table 1 presents descriptive statistics on EMR use, overall and by level of EMR sophistication. EMR use in hospital-based EDs was limited in 2006. Although one half (46.2%) of EDs used any EMR system, EMR sophistication varied considerably. While most EDs (87.5%) had less than a minimum set of EMR functions, only 10.8% had a basic EMR, and only 1.7% had a fully functional EMR.[10] EMR use also varied for specific functions. Nearly all EDs had electronic patient demographic information (95.2%) and laboratory results (89.3%). However, few EDs had EMR capabilities for electronic images returned (42.1%) and reminders for guideline-based interventions and/or screening tests (31.8%).

We found some association between hospital and area characteristics and the level of EMR sophistication.[11] Relative to minimal/no EMR, hospitals with basic EMR and fully functional EMR were more likely to be located in metro areas with higher median household income and educational attainment. Hospitals with fully functional EMR were more likely to be located in the Midwest region. In the multivariate analysis (Table 3), ownership and urban–rural classification had a significant relationship with EMR use in the ED. Government and for-profit hospitals were more likely to have minimal/no EMR, relative to voluntary/nonprofit hospitals. Hospitals located in small metro areas were more likely to have basic EMR.

EMR Sophistication and ED Length of Stay

Fully functional EMR was associated with lower LOS (Table 4). On average, EDs with fully functional EMR had 22.4% lower LOS than EDs with minimal/no EMR. Fully functional EMR had a negative and significant relationship with LOS for admitted and discharged patients. Fully functional EMR was associated with 23.5% lower LOS for patients admitted to the hospital and 21.3% lower LOS for patients discharged home. Relative to Basic EMR, fully functional EMR had significantly lower LOS.

On average, we found no significant relationship between basic EMR and LOS, overall or by visit disposition. However, our sensitivity analysis revealed that basic EMR had a nonlinear relationship with LOS. For patients admitted to the hospital, EDs with basic EMR consisting of 6 to 9 (10 or 12) functions had significantly higher (lower) LOS than EDs with minimal/no EMR.

Table 3. Hospital and Area Characteristics Associated With EMR Sophistication

	Minimal or No EMR	Basic EMR	Fully Functional EMR
Government, non-Federal	.037* (.021)	−.036* (.020)	−.002 (.001)
Proprietary, for-profit hospital	.050** (.022)	−.048** (.021)	−.002 (.001)
Teaching hospital	.029 (.026)	−.028 (.024)	−.001 (.002)
Hospital with critical care unit	.000 (.027)	.000 (.026)	.000 (.001)
Percentage of ED visits, admitted to hospital	.000 (.002)	.000 (.001)	.000 (.000)
Percentage of ED visits, immediate/emergent	.000 (.000)	.000 (.000)	.000 (.000)
Percentage of ED visits, nonurgent/no triage	.000 (.000)	.000 (.000)	.000 (.000)
Region, Northeast	−.028 (.057)	.026 (.054)	.001 (.003)
Region, South	.012 (.045)	−.012 (.042)	−.001 (.002)
Region, West	−.017 (.048)	.016 (.046)	.001 (.002)
Urban-rural, large fringe metro	−.108 (.079)	.100 (.071)	.008 (.009)
Urban-rural, medium metro	−.131 (.093)	.121 (.083)	.010 (.012)
Urban-rural, small metro	−.193** (.079)	.176** (.068)	.017 (.014)
Urban-rural, nonmetro	−.102 (.104)	.095 (.095)	.007 (.011)
Urban-rural, missing	−.086 (.126)	.080 (.115)	.006 (.012)
Median household income, $32,794 to $40,626	.038 (.029)	−.036 (.027)	−.002 (.002)
Median household income, $40,627 to $52,387	−.102 (.088)	.095 (.082)	.007 (.008)
Median household income, $52,388 or more	−.196 (.152)	.178 (.129)	.018 (.025)
Percentage college educated, 12.84% to 19.66%	.016 (.032)	−.015 (.031)	−.001 (.001)
Percentage college educated, 19.67% to 31.68%	.031 (.035)	−.030 (.034)	−.001 (.002)
Percentage college educated, 31.69% or more	.042 (.034)	−.040 (.032)	−.002 (.002)
Area characteristics, missing	−.084 (.116)	.078 (.106)	.006 (.011)
EMR system includes public health reporting only	−.209** (.087)	.188** (.078)	.021 (.014)
EMR system includes public health reporting and notifiable diseases sent electronically	−.495*** (.115)	.391*** (.085)	.105* (.053)
Instrument relevance test (*F* statistic)	22.8		
N	364		

Note: EMR = electronic medical records; ED = emergency department. Marginal effects from survey-weighted ordered probit regression. Standard errors in parentheses.
***$p < .01$. **$p < .05$. *$p < .10$.

Table 4. Association of EMR Sophistication With ED Throughput and Left Without Treatment

	Basic EMR	Fully Functional EMR
ED length of stay		
All patients	.029 (.045)	−.224**,b (.110)
Admitted to hospital	−.083 (.076)	−.235** (.096)
Discharged home	.048 (.049)	−.213*,b (.123)
Wait time to see a physician		
All patients	.142* (.076)	−.641c (.448)
Immediate/emergent	.304** (.144)	−.427c (.397)
Urgent/semiurgent	.473*** (.173)	−.210 (.709)
Nonurgent/no triage	.002 (.122)	−.620**,b (.273)
Diagnosis and treatment time		
All patients	.007 (.054)	−.131**,c (.060)
No diagnostic services	.078 (.084)	.053 (.094)
Any diagnostic service, no imaging	−.103 (.074)	−.024 (.095)
Any imaging procedure	.016 (.047)	−.264***,a (.058)
Left without treatment		
All patients	.002 (.004)	−.007 (.008)
Emergent	.005 (.005)	−.006***,b (.002)
Urgent	−.001 (.005)	.002 (.012)
Nonurgent	.007 (.009)	−.013 (.015)

Note: EMR = electronic medical records; ED = emergency department. Marginal effects relative to minimal/no EMR. Standard errors in parentheses, significant at ***$p < .01$, **$p < .05$, *$p < .10$. Tests of linear restrictions, Basic EMR = Fully functional EMR, significant at [a]$p < .01$, [b]$p < .05$, [c]$p < .10$. Full regression results are available on request from the author.

EMR Sophistication and ED Wait Time

Greater EMR sophistication was associated with higher and lower wait time to see a physician (Table 4). Relative to minimal/no EMR, basic EMR had a positive and significant relationship with wait time. In contrast, fully functional EMR was associated with significantly lower wait times relative to basic EMR and relative to minimal/no EMR.

We found that the relationships between EMR sophistication and wait time differed by patient acuity level/triage, basic EMR had 30.4% higher wait time for patients with Immediate/Emergent acuity and 47.3% higher wait time for patients with Urgent/Semiurgent acuity. For patients with Nonurgent/No triage acuity, fully functional EMR was associated with 62.0% lower wait time, and basic EMR had a nonlinear relationship with wait time.

EMR Sophistication and ED Treatment Time

Fully functional EMR was associated lower diagnosis and treatment time (Table 4). EDs with fully functional EMR had 13.1% lower treatment time than EDs with minimal/no EMR.

The relationship between EMR sophistication and treatment time varied by the diagnostic services provided. We found little relationship between fully functional EMR and treatment time for patients with no diagnostic service or patients with any diagnostic service except imaging. However, a strong relationship was found between fully functional EMR and treatment time for patients with any imaging procedure. Fully functional EMR had significantly lower treatment times relative to basic EMR and relative to minimal/no EMR.

On average, we found no significant association between basic EMR and treatment time, overall or by diagnostic services provided. However, the relationship between the number of EMR functions used and treatment time was nonlinear. For patients with any diagnostic service except imaging, EDs with basic EMR consisting of 6 to 9 (10-12) functions had significantly lower (higher) treatment times than EDs with minimal/no EMR.

EMR Sophistication and Left Without Treatment

On average, fully functional EMR had no significant relationship with LWOT (Table 4). However, the relationships differed by patient acuity level/triage. For patients with Immediate/Emergent acuity, fully functional EMR had significantly lower LWOT relative to basic EMR and relative to minimal/no EMR (–0.6%).

On average, basic EMR had no significant relationship with LWOT, overall or by patient acuity level. However, the relationship between basic EMR and LWOT varied nonlinearly by the number of EMR functions used.

Discussion

We found that greater EMR sophistication had a mixed association with ED efficiency. On average, EDs with fully functional EMR had significantly lower LOS and treatment times than EDs with minimal/no EMR. These findings were consistent with case studies at single institutions documenting benefits from specific EMR functions. CPOE implementation at an urban, university-affiliated hospital was associated with significantly lower LOS for discharged patients (Spaulding, Mayer, Ginde, Lowenstein, & Yaron, 2008). At a large urban tertiary referral center, the Emergency Department Information System and process redesign were associated with significantly lower LOS, wait time, and treatment time (Weiner, Shapiro, & Baumlin, 2007).

The relationships between EMR sophistication and ED efficiency varied by visit disposition, patient acuity level, and diagnostic services provided. Lower LOS for admitted patients suggests that EMR might facilitate bed management, which may alleviate boarding. Lower LOS for discharged patients implies that EMR might speed throughput for low-complexity patients. Lower waiting times for nonurgent patients could reflect automated triage and/or access to patient information from prior visits, which might speed registration. Lower treatment times for patients with any imaging procedure could reflect faster turnaround times because of PACS and/or CPOE (Henstrom, Norton, & Fu, 2007).

Besides the inherent benefits of EMR, the association of fully functional EMR with higher ED efficiency might also reflect the characteristics of the adopters themselves as well as contextual/managerial factors within the organization (Berwick, 2003). Hospitals with fully functional EMR were located in large urban and affluent areas, which may confer financial/human resources that enable them to be technology innovators. A favorable patient population (more children, White, privately insured) and moderate acuity levels also support an environment conducive to IT adoption and organizational change.

Surprisingly, basic EMR was associated with higher wait times on average, especially for patients with Urgent/Semiurgent acuity. However, the relationships between basic EMR and ED efficiency varied nonlinearly with the number of EMR functions used. Several explanations might account for this finding. First, some EMR functions (CPOE, Nursing Documentation) might decrease efficiency by increasing provider time spent on a computer (Asaro & Boxerman, 2008; Banet, Jeffe, Williams, & Asaro, 2008; Malhotra et al., 2008; Yen et al., 2008). Second, basic EMR might reflect only partial automation of ED processes and may not require behavioral changes associated with advanced decision support functions. Systems with part electronic and part paper may be incomplete and fragmented, with redundant log-ins and displays that can induce workarounds, errors, and dissatisfaction (Koppel et al., 2005). Third, hospitals with basic EMR may still be engaged in the implementation process, and disruptions to workflow because of implementation itself may overshadow any enhancements to efficiency.

Implications for Policy and Practice

The finding that the level of EMR sophistication matters has important implications for the policy debate over "meaningful use" of EMR. Our results imply that basic EMR is not sufficient and that fully functional EMR may be necessary for gains in efficiency. Thus, to realize the goal of improved efficiency, incentives for EMR adoption in EDs should be sufficient to achieve use of fully functional EMR systems.

The finding of variation in efficiency by the level of EMR sophistication has important implications for practice. Our results suggest that basic EMR may imply a learning curve as hospitals face difficulties with implementation of advanced functionalities (Jha et al., 2009). The finding that EMR varied across different types of ED visits suggests that expectations might be targeted toward specific subprocesses (e.g., triage, discharge planning). Our finding that fully functional EMR was not associated lower LWOT (with one exception) implies that technology alone is insufficient to address this important challenge.

Our findings raise an important question for future research: Are improvements in ED efficiency because of technology itself or associated changes in processes? In an American College of Emergency Physicians (2007) survey, 76% of respondents said patient flow technology could relieve ED overcrowding, provided that it was accompanied by process and staff changes; however, only 17% indicated technology on its own could address patient flow and overcrowding. As EMR systems mature and diffuse, further research should investigate the role of EMR as an enabler versus a catalyst for the redesign of inefficient processes.

Limitations

Our study has some limitations. Although we found almost no evidence of endogeneity, we could not infer a causal relationship between EMR use and ED efficiency. Our cross-sectional analysis examined the association between the level of EMR sophistication and efficiency at a single point in time. Since NHAMCS lacked a longitudinal design, we were unable to examine EMR implementation in relation to changes in efficiency over time. Although we controlled for many determinants of efficiency, EMR adopters may differ in characteristics and context that we could not observe in the data, and our estimates may remain biased from these confounding factors.

Our focus on EMR use was limited in scope. While the NHAMCS reported any use of EMR functions, we could not observe "how" the EMR was used. Evidence suggests that human factors design (Asaro, Sheldahl, & Char, 2006; Reingold & Kulstad, 2008) and wireless technology (Bullard, Meurer, Colman, Holroyd, & Rowe, 2004; Shannon, Feied, Smith, Handler, & Gillam, 2006) can influence system utilization. We were unable to measure the status of EMR implementation, software maturity or systems integration, user acceptance and satisfaction, or the extent of organizational change and workflow redesign. We note our EMR variables did not capture the presence of an electronic whiteboard for patient tracking, EMR use in hospital units outside of the ED, and interoperability with community providers.

Finally, our study did not consider related issues of importance. We were unable to examine whether EMR was associated with crowding per se, boarding, or ambulance diversion; hospital costs and revenues; provider and patient satisfaction; or patient health outcomes. These are important subjects for further research.

Conclusions

EMR use in U.S. hospital emergency departments was limited in 2006; very few EDs had fully functional EMR systems.[12] Greater EMR sophistication had a mixed association with ED efficiency. On average, EDs with fully functional EMR had significantly lower LOS and lower treatment time, relative to EDs with minimal/no EMR and basic EMR. However, the relationships between EMR and efficiency varied by patient acuity level and diagnostic services provided. Surprisingly, EDs with basic EMR were not more efficient on average, which could imply a learning curve where the benefits to ED efficiency vary nonlinearly with the number of EMR functions used.

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Notes

1. Asplin et al. (2003) mention IT as an operational solution to crowding; however, their model does not explicitly include IT or EMR.
2. Comprehensive EMR was defined as a system with electronic functionalities in *all* clinical units, including the ED (Jha et al., 2009). Thus, inpatient EMR is implicitly assumed to be hospital-wide.
3. Hausman tests of endogeneity were conducted using two-stage residual inclusion (2SRI) regression models (Terza, Basu, & Rathouz, 2008). Generalized residuals were calculated from first-stage ordered probit regressions predicting EMR sophistication. *T* tests on the significance of the residual term in second-stage OLS regressions were a test of endogeneity. The residual term was not significant at $p < .05$ in all regression models, with one exception. Endogeneity of EMR was indicated in the wait time model for patient acuity/triage of Urgent/Semiurgent ($p = .016$), and estimates from 2SRI were reported for this measure. Naive OLS estimates were reported for all other measures. Results of the endogeneity tests are available on request from the author.
4. Overidentification tests were conducted using Hansen's *J* statistic, which tested the null hypothesis of exogeneity of the IVs. Exogeneity was not rejected at significance of $p < .05$ in all regression models. Results of the overidentification tests are available on request from the author.
5. Because of small sample sizes, left without being seen and left against medical advice were grouped together as LWOT.
6. Missing records accounted for 6.1% of LOS, 18.9% of wait times, and 21.0% of treatment times.
7. These measures were based on the ED Comparison System developed by a consensus group (Welch, Augustine, Camargo, & Reese, 2006). This system stratifies hospitals based on volume and acuity levels (i.e., admission rate > 20%) for benchmarking ED performance.
8. Stata 10.1 lacked a program to directly compute standard errors from two-step estimation that accounted for the complex survey design. Estimations accounting for the sampling weights but not clustering and/or stratification in the sampling plan will lead to standard errors that are underestimated (Shih & Konrad, 2007). For 2SRI models, a two-step bootstrapping procedure was applied that used replicate weights to resample within primary sampling units (Rao & Wu, 1988). First, bootstrap replication weights were calculated using -bsweights-. Second, standard errors were bootstrapped for 500 replications using -bs4rw-.
9. Results from the sensitivity analysis are available on request from the author.

10. Although the sample of EDs with fully functional EMR was small ($n = 10$), complex survey weights allowed inference to be made on the weighted sample ($n = 79$), which was nationally representative (Korn & Graubard, 1999).
11. Descriptive statistics for patient, visit, hospital and area characteristics stratified by EMR sophistication are available on request from the author.
12. Our 1.7% estimate was similar to a national survey, which found that only 1.5% of U.S. hospitals had comprehensive EMR implemented in all major clinical units (Jha et al., 2009).

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