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Effects of Electronic Health Record Adoption on Hospital Cardiac Risk-adjusted Mortality Rates

- Patients with Acute Myocardial Infarction or Congestive Heart Failure

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Bachelor of Business Administration
Chung Chan Medical University
2005

Thesis Committee Chair: David H. Howard PhD

An abstract of
A thesis submitted to the Faculty of the
Rollins School of Public Health of Emory University
in partial fulfillment of the requirements for the degree of
Master of Sciences in Public Health
in Health Policy and Health Services Research
2011

Abstract

Effects of Electronic Health Record Adoption on Hospital Risk-Adjusted Mortality Rates - Patients with Acute Myocardial Infarction or Congestive Heart Failure

By Peiyin Hung

Background: The final rule from CMS for the meaningful use of electronic health records (EHR) leaves unanswered basic questions about how the implementation of different EHR subsystems and the sequence of the implementation influence various treatment outcomes.

Methods: This study examines the impact of five EHR subsystems on risk-adjusted mortality rates (RSMRs) in patients with AMI or CHF. 969 non-federal, acute care hospitals in 12 states were extracted from the linked 2008 American Hospital Association EHR Survey and CMS Hospital Compare Database. Adjusting for major hospital characteristics using least squares regression and propensity scores, we analyzed the impact of both EHR subsystem adoptions and the number of adopted EHR subsystems (clinical documentation, test results viewing system, physician order entry, decision support, bar-code system) on the outcomes of AMI and CHF inpatients.

Results: Significant variation exists in the implementation of EHR subsystems across U.S. hospitals. The presence of an EHR in a hospital resulted in significant reductions in RSMRs for both AMI and CHF by as much as 0.59%. Adopting an additional subsystem resulted in reductions in AMI and CHF RSMRs; however, optimal results were achieved in AMI and CHF when hospitals fully adopted at least 3 and 5 subsystems, respectively. Of all EHR subsystems, computerized physician order entry is the most significant.

Implications: Policies to encourage adoption of EHR should emphasize computerized physician order entry and consider the sequence of EHR subsystem adoption in hospitals.

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LIST OF ABBREVIATIONS

AHA- American Hospital Association

AHRQ- Agency for Healthcare Research and Quality

AMI- Acute Myocardial Infarction

ANOVA- One-way Analysis of Variance

ARRA- The American Recovery and Reinvestment Act

CHF- Congestive Heart Failure

CMS- The Centers for Medicare and Medicaid Services

CPOE- Computerized Physician Order Entry

ECD- Electronic Clinical Documentation

EHR- Electronic Health Record

HIPPA- The Health Insurance Portability and Accountability Act

HIMSS- The Health Information Management Systems Society

HITECH-Health Information Technology for Economic and Clinical Health

IOM- Institute of Medicine

OLS- Ordinary Least Squares

PACS- Picture Archiving and Communication Systems

RSMRs- Risk-adjusted 30-day Mortality Rates

VA- Department of Veterans Affairs

VIF- Variance Inflation Factor

INTRODUCTION

To date, efforts to improve patient outcomes have turned toward electronic health record system (EHR) adoptions. Along with the American Recovery and Reinvestment Act (ARRA) and its important Health Information Technology for Economic and Clinical Health (HITECH) Act passed in 2009, health care organizations started to focus on facilitating the EHR adoption and meeting the meaningful use criteria to receive the financial incentives set forth by those Acts.

In executing the legislation, health outcomes and care performance play an essential role. The performance and patient care outcomes must be improved to meet meaningful use criteria. A certified EHR system is also required. However, the final rule of the meaningful use criteria leaves unanswered critical questions about how the implementation of different EHR subsystems, the sequence of the implementation and the adoption status of an EHR system influence various treatment outcomes.

Implementing an EHR system is complicated and intricate, especially in an inpatient setting of a hospital. To determine the actual impact of an EHR, many health care outcomes can be examined. This study aims to provide the ultimate effects on vulnerable patients. By using risk-adjusted mortality rates as the outcomes, this study will mainly answer how the implementation of EHR subsystems influences outcomes of patients with acute myocardial infarction or congestive heart failure.

LITERATURE REVIEW

Background and Overview

In 2009, the U.S. Congress passed the HITECH Act which will spend $19.2B to encourage the adoption of EHRs by physicians and hospitals.[1] Under the Act, the Centers for Medicare and Medicaid Services (CMS) expect eligible professionals and hospitals to demonstrate meaningful use of a certified EHR, the electronic exchange of health information to improve the quality of health care, and methods of reporting on clinical quality and other measures using certified EHR components.

There is no standardized EHR definition, nor is there a widely-accepted term to describe computerized health information in a hospital setting.[2-7] In the HITECH Act enacted, a qualified EHR is defined as "*an electronic record of health-related information on an individual that: (A) Includes patient demographic and clinical health information, such as medical history and problem lists; and (B) has the capacity: (i) To provide clinical decision support; (ii) to support physician order entry; (iii) to capture and query information relevant to health care quality; and (iv) to exchange electronic health information with, and integrate such information from other sources*."[8]. Simply stated, an EHR is established to generate a complete record of a clinical patient encounter and to support health care services via computerized interfere.[2,6] Studies about EHR rarely identify which version of the EHR definition the authors employed leading to ambiguity in terms of implementation and meaningful use.[9, 10]

An EHR has numerous ancillary subsystems that collectively serve as an efficient way to record patient data within a health facility. Although EHRs have different usages among hospitals, its ancillary subsystems primarily consist of computerized physician order entry, decision support systems, electronic clinical documentation, barcode systems, and laboratory/radiology test results viewing systems.

Computerized Physician Order Entry [i]

Computerized physician order entry serves as a major component for an EHR. This component offers a variety of functionalities from pharmacy ordering capabilities to complete ancillary service ordering, alerting, and result reporting.[2] These order-entry systems are automatically linked to patients' health records or clinical decision support systems to provide evidence-based recommendations on drug administration and other services, including follow-up treatment and reminders for preventive care.[11]

Decision Support System

Decision support subsystems provide the EHR system with a patient's prescription information and clinical guidelines.[2] These information systems were designed to assist physicians in deciding appropriate medication type, dosage and frequencies, according to the patient's health status and existing medical history as stored in the EHR.[2]

Electronic Clinical Documentation[ii]

The clinical documentation component provides electronic documents of medication lists, clinical notes, patient assessment summaries, and clinical reports that could allow clinical providers to better assess the condition of their patients.[2]

Barcode System

The barcode subsystem provides patient identification and tracks pharmaceuticals. At the bedside, the use of barcode technology to verify a patient's identity and the medication to be administered is a promising strategy for preventing medication errors and its use has been increasing, most notably in Veterans Affairs hospitals.[13] A barcode system at the bedside is usually implemented in conjunction with an electronic medication administration system, allowing nurses to automatically document the administration of drugs by means of barcode scanning.

Laboratory Test Reviewing Functionality[iii]

The laboratory subsystem provides EHRs with laboratory test results for access by health care providers. Radiology subsystems are used by radiology departments to tie together patient radiology data and images. The function of radiology information systems include scheduling, patient tracking, results reporting, and image tracking.[2] Most radiology departments use multiple electronic systems to access information.

Prevalence of Electronic Health Record

The implementation of EHRs has been very slow since 2003, when the Health Insurance Portability and Accountability Act (HIPPA) set a goal for national adoption in the United States.[14-16] The top three reasons for the delays are primarily financial: inadequate capital for purchase, unclear return on investment, and maintenance costs.[14]

Ashish K. Jha and his colleagues compared seven countries' states of health information technology adoption in 2008. While the adoption and use of EHR systems in the hospital setting was in its early stage among all sampled nations, the United States was far behind other industrialized nations in adoption of EHRs in the ambulatory care setting.[17]

Although a further study showed modest gains in EHR adoption between 2008 and 2009 in the United States, from 1.5 percent to 2.7 percent of hospitals utilizing comprehensive EHRs, only 11.9 percent of U.S hospitals had EHR systems in place in at least one unit.[18] Researchers identified the two components that are most challenging to adopt--computerized physician order entry for medications and electronic physician notes. Approximately one-third of hospitals had fully implemented these functions in one or more major clinical units. However, 40 percent of U.S. hospitals reported having no firm plans to adopt these functions.[18]

Despite the increased prevalence of EHR adoption in the U.S., there are wide differences in implementation among hospitals. Studies have shown that hospital size, profit status, teaching status and location alter the state of EHR adoption, but hospital system membership does not.[18] However, relatively little is known about the impact of EHR adoption on hospital medical practices, financial characteristics and staffing levels.

Electronic Health Record and Healthcare Quality

Since the Institute of Medicine published the book, “To Err is Human,” (1999) health care experts, policymakers, payers and consumers have considered EHRs to be critical to improving quality of care.[19] Many studies have thus focused on using EHRs to improve the quality of health care,[20] but results were mixed on the association between EHR systems and health care quality.

There is wide agreement among studies on a positive association between EHRs and health care quality in other health care settings.[21-26] For example, Athey [24] used panel datasets of Pennsylvania counties between 1994 and 1996 to assess the effect of a health information technology on patient health measured at the time of ambulance arrival. They found a positive impact and suggested that information technology speeds up emergency response, reduces mortality, and lowers costs. Another study addressed the issue of increasing certainty on EHR investments by using simulations to estimate the costs and benefits of EHR system adoption and arrived at a similar conclusion. [27]

Notably, studies about EHRs and their effects have mostly been undertaken in large hospital settings, such as in the Department of Veterans Affairs (VA) system. [28-34]

The Department of Veteran Affairs is a broad-based national health care system and has been using electronic health records since the mid 1980s.[35] Byrne and his colleagues found that the VA, with its EHRs, had higher preventive performance during 2004–2007 relative to the private sector, in terms of decreased utilization/services for diabetic patients.[29]

Nevertheless, most of the aforementioned studies were case studies that only assessed a single facility [21, 33] or specific units of a single hospital.[24, 26, 28, 36] Studies that had a larger sample size were mostly focused on particular subsystems of electronic health record (e.g. computerized physician order entry or decision support system.) [10, 20, 22] For instance, McCullough et al evaluated changes in the quality of care following the adoption of electronic health records. The authors, based on their assessment of a national sample of the United States hospitals from 2004 to 2007, concluded that the use of computerized physician order entry resulted in significant improvements in preventative quality measures for hospitalized patients who contracted pneumonia.[20] However, the study failed to address the impact of a comprehensive EHR adoption. (i.e. full adoption across all units in a hospital) This may be due to the fact that only 1.5 percent of U.S hospitals had adopted comprehensive EHR systems before 2009. [14]

In addition to studies on computerized physician order entry, studies were conducted to assess the impact of a decision support system upon physician prescribing behavior by measuring either the rate of compliance on recommended therapeutic decisions provided by order entry systems, or the effect on patient outcomes such as adverse drug events and length of hospital stay.[37] Decision support subsystem related studies were mainly time-series or pre-post studies, where the rates of adherence to clinical guidelines were compared before and after the intervention periods.[38] During the control period, standard clinical guidelines (usually with limited functionality) were used, and additional functions such as reminder and decision support were added during the intervention period.[38-40] Among these studies, there were no consistent results on the impact of a decision support system on quality measures.

Yet, it has been shown in several studies that the use of an electronic clinical documentation is conducive to more complete and accurate documentation by health care professionals.[11, 41, 42] For the barcode system, previous studies have shown that this technology can prevent errors in dispensing drugs from the pharmacy [8] and in counting sponges in the operative setting. [43]

Studies conducted to assess the impact of the laboratory subsystem on patient outcomes are limited. Laboratory-result studies are primarily time series studies, where rates of clinical compliance are compared between electronic and paper-based systems.[26] In addition, a randomized controlled trial study was conducted to assess the accuracy of identifying people with diabetes by the EHR application; the authors, based on their experience in Ontario, suggested using the laboratory functionalities to improve patients' quality of care.[44] However, these studies were set in a single facility.

In contrast, a few studies did not conclude positive effects of EHRs. For instance, a study performed in a tertiary-care hospital during 2002 and 2004 found that computerized physician order entry increased medication errors. [45] Studies have shown that information overload represents one of the major challenges of applied health informatics, with the cognitive burden hampering treatment planning and quality of care, which leads to poor patient outcomes. [46, 47]

In October of 2009, Ashish K. Jha et al. compared approximately 3000 hospitals at various stages (fully adopted, partially adopted and not yet adopted) during the adoption of computerized health records and found no consistency in the quality of care outcomes.[48] Furthermore, a new study published in the Archives of Internal Medicine showed that the use of EHR and clinical decision support tools do not significantly improve the quality of care in outpatient visits.[49]

Notably, Shereef et al. found the positive correlation between hospitals' quality of care in 2006 and EHR adoption in 2009 among the U.S. hospitals. This study suggests that an EHR adoption is more prevalent among high-quality hospitals[50]- the importance of adjusting preliminary differences between hospitals with and without an EHR adoption in the evaluation of how an EHR adoption impacts healthcare quality was shown. Yet, limited existing studies have addressed such potential sources of selection bias.

In addition, although a majority of researchers agree there exists a positive correlation between an EHR adoption and quality of care, quality indicators varied across studies. The quality measures in the studies are either provider outcomes (e.g. proportion of appropriate prescription) [25, 41, 44, 45], or patient outcomes (e.g. adverse drug events).[45, 51-53] Few studies examined the impact of EHRs on mortality rates, such ultimate measures are essential to patients. Thus, studies on whether EHR adoption has significant positive associations with healthcare quality in a common trend are still exploratory.

Acute Myocardial Infarction & Congestive Heart Failure Mortality

In examining healthcare quality, it is essential to define and measure uniform standardized quantifiable indicators across the practice setting. One such set of healthcare indicators is AMI or CHF patient's risk-adjusted mortality rates- which have been shown a benchmark of healthcare quality. Also, both AMI and CHF are leading causes of morbidity and mortality worldwide. In 2006, about 1 in 200 people in the United States suffered an AMI and 1 in 55 people suffered from CHF. Of the over 6 million cases, 831,272 cases ended in fatalities, accounting for 34.3 percent of all deaths in the United States. [54] Health care professionals, consumers, and payer organizations have sought to improve outcomes for patients hospitalized with AMI and CHF.[55] Meanwhile, the federal government identified cardiovascular conditions as a priority area for the public reporting of hospital-based outcome measures. [56] Despite these advancements, opportunities to further improve care of AMI or CHF still exist. Little is known about the current extent of variation among hospitals' improvement after national efforts were developed.

Notably, AMI or CHF mortality correlates to some hospital characteristics such as geography, teaching status, volume of cases, and staffing levels. In 1992, Schultz [57], based on their assessment of two-thirds of the hospitals in California, concluded that registered nurses staffing levels and availability of Coronary Artery Bypass Graft /or Percutaneous Transluminal Coronary Angioplasty was inversely related to mortality of patients with AMI, while hospital financial factors (e.g. total operating expenses/patient day) was positively related to mortality. Other studies suggest that there is an urban-rural disparity on the AMI/CHF mortality.[58-60] In addition, a study conducted in 2008 to assess measurements and tools focusing on several diseases, including CHF, showed that integrating EHR into more physician offices would result in more accurate measurements and documentations of diagnoses and care procedures.[61]

In 2003, the CMS initiated an ongoing national effort to measure and improve hospital care for patients with AMI and CHF. Most studies just used the measures to test the validity of Medicare claims data and to compare the structural and financial characteristics of hospitals. [57, 60, 62-66] Despite widespread enthusiasm for EHRs as a tool to help transform quality and patient safety, to date limited published study results have associated EHR implementation with significant reductions in hospital-wide mortality rates of patients with AMI or CHF.

Previous Study Limitations

To reiterate, the aforementioned studies have significant limitations. The major limitations are: 1) use of partial electronic health record functions, 2) limited to a single practice setting for analysis, 3) use of different terms for health information technology without accounting for the functionality, and 4) use intermediate measures as the outcome.

To fill the gap of the major drawback in the literature that fails to assess both distinct EHR functions and the impact in a large number of hospital settings, this study analyzed the effects of adopting five distinct EHR subsystems on the AMI or CHF risk-adjusted mortality rates.

METHODOLOGY

This study examines the effects of EHR adoption and the distinct EHR subsystems on mortality rates of Medicare patients with acute myocardial infarction and congestive heart failure. The overall analysis has two phases: the first part focuses on the probability of EHR adoption among hospitals, given major hospital characteristics; the second piece focuses on mortality-rate estimates incorporating various statuses of EHR subsystems' adoption.

The study hypotheses (H*i*) are:

H1: Hospitals with EHR adoption have lower mortality rates.

H2: Hospitals with more fully implemented subsystems have lower mortality rates.

H2a: Hospitals with electronic clinical documentation have lower mortality rates.

H2b: Hospitals with a fully implemented test results viewing system have lower mortality rates.

H2c: Hospitals with fully implemented computerized physician order entry in more units have lower mortality rates.

H2d: Hospitals with a fully implemented decision support system will have lower mortality rates.

H2e: Hospitals with a fully implemented barcode system will have lower mortality rates.

H3: Hospitals with a fully implemented subsystem in more units have lower mortality rates.

Study Design

Data Source

This study utilizes three primary sources of data to create key variables of interest: the American Hospital Association (AHA) Hospital Annual Survey of U.S. acute care hospitals [67] for 2005 and 2008, the AHA Hospital EHR Adoption Database for 2008, and the Centers for Medicare & Medicaid Services (CMS) Hospital Compare Dataset from 2005 to 2009 [68]. [Table 1]

Table 1. Data Sources Information

Dataset sources	Year	Variables	Number of Hospitals	Hospital Identifier
AHA Hospital Annual Survey	2005 and 2008	Hospital characteristics: clinical services and financial predictors	4,335 hospitals	AHA provider ID and Medicare Provider ID
AHA Hospital EHR Adoption Database	2008	1.Presence and components of EHR 2.Hospital characteristics: city, state, staffed beds	3,720 hospitals	AHA provider ID/ Hospital Name
Centers for Medicare & Medicaid Services (CMS) Hospital Compare Dataset	2005-2010	1. Hospital characteristics 2. Risk-adjusted 30-day mortality rates (RSMRs) for AMI and CHF	4,157 hospitals	Medicare Provider ID/Hospital Name

The AHA Annual Surveys were sent to the hospital chief executive officers. The overall response rate for the survey was approximately 80% in 2005 and 85% in 2008, both of which are quite high for a voluntary survey of its length. From this survey, explanatory variables concerning hospital demographics, organization structure, and clinical services were created. AHA Annual Survey data was linked to data from the AHA EHR Database to obtain further information on hospital characteristics and EHR functionality.

Since 2007, the Hospital EHR Adoption Survey has been presented as an information technology supplement to the association’s annual survey of members. The survey includes questions about hospital policies and structures, including multiple questions regarding the presence and components of an EHR. Hospital characteristics, including city, state, staffed bed size and other EHR-related factors, were used for either exclusion criteria or outcome predictors. The response rate for the 2008 survey was 77%, for a total sample size of 3,720 hospitals.

CMS has published hospital-specific 30-day mortality rates for patients with AMI and heart failure since 2004 and updates these rates annually. These measures are determined using administrative claims and medical records data. The cohorts for 30-day AMI/CHF risk-standardized mortality rates (RSRMs) are hospitalizations for fee-for-service Medicare patients who are more than 65 years old and who have been enrolled in FFS Medicare for the 12 months prior to the hospital admission being measured for the outcome. In this study, we included hospitals' reported RSMRs for the discharges that occurred from July 1, 2008 to June 30, 2009. Patients were identified for having either acute myocardial infarction or heart failure, based on patients' principal discharge diagnosis. The 30-day mortality measure counts deaths for any cause, in any location, within 30 days of the hospital admission date. CMS used hierarchical logistic regression models for each condition to account for the hierarchical structure of the data and the similarity of outcomes within a hospital that may be due to hospital quality. Each hospital's RSMR is similar to an observed-to-expected ratio that is then multiplied by the national average so that rates, rather than ratios, are reported.

Additional hospital characteristics were selected from the CMS data for explanatory variables. These characteristics are often used as implicit measures of hospital quality and are known to affect patient outcomes. For this study, we merged the CMS Hospital Compare data for 2005-2010 with the data from the 2005 and 2008 AHA EHR Surveys, as well as the 2008 AHA Annual Survey Database, using specified hospital identifiers.

Study Sample

Due to resource limitations, we extracted hospitals in 12 states (CA, IL, IN, MA, MI, MN, MO, NY, OH, PA, TX, and WA) from the 2008 AHA EHR Dataset. All acute care hospitals in these states with a Medicare provider ID were included in our analysis. In the CMS dataset, hospitals were excluded if all of the measures they reported were based on fewer than 25 patients in the given year. After merging the aforementioned three datasets, the sample available for this analysis was 969 hospitals. It encompasses approximately 24% of the non-federal, acute care hospitals in the United States.

Conceptual Framework

The conceptual framework [Figure 1] outlines the salient factors when considering electronic health record system (EHR) adoption and condition-specific RSMRs for hospitals.

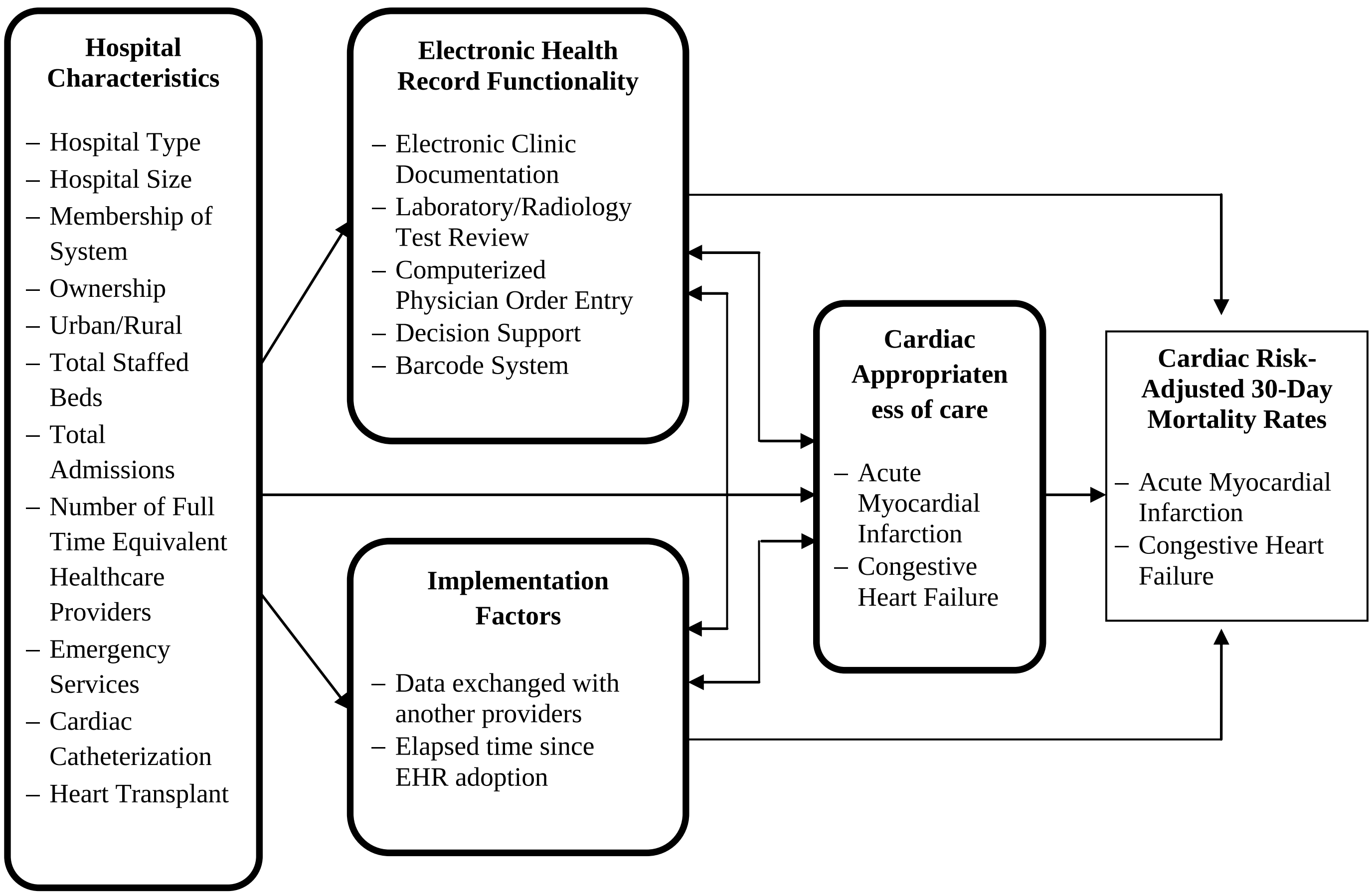


Figure 1. Conceptual Model for This Study

In order to determine whether adopting each of five primary EHR subsystems (electronic clinical documentation, test results viewing systems, computerized physician order entry, decision support, and barcode systems) influences outcomes, we created two kinds of independent variables: the presence of subsystems, and the adoption status of the subsystem (e.g. adoption across all units, in at least one unit or none). According to existing studies, we believe that EHR adoption varies by hospital characteristics. Additionally, an EHR adoption along with the implementation factors is assumed to affect cardiac appropriateness of care and further to impact the hospital cardiac mortality rates. Outcomes were measured by condition-specific 30-

day mortality rates of hospitalized patients with acute myocardial infarction or congestive heart failure at the hospital-level.[Figure 1]

Dependent Variables

There are two dependent variables in this analysis reflecting two different conditions (acute myocardial infarction and congestive heart failure). The two condition-specific outcome variables are the risk adjusted percentage of total deaths of patients hospitalized with acute myocardial infarction (AMI), and the percentage of total death of patients hospitalized with congestive heart failure (CHF) in a hospital in 2009. These variables are continuous and can range from 0% to 100%.

Key Independent Variables

Status of Electronic Health Record Subsystem

We focused on five primary subsystems described in the AHA EHR survey: computerized physician order entry, the decision support system, electronic clinical documentation, the barcode system, and the test result viewing system. Our data noted the presence or absence of 32 clinical functionalities of an electronic record system, and whether the hospital:

1) Had fully implemented these functionalities in all major clinical units,
2) Had implemented them in one or more (but not all) major clinical units,
3) Began implementation in at least one unit,
4) Had resources for implementation in the next year,
5) Did not have resources but was considering implementation, or
6) Did not have resources and was not considering implementation.

We then classified the statuses [Figure 2] of subsystems by the presence of relevant functionalities in each subsystem. The definitions of relevant functionalities were created by an expert panel from the 2008 AHA IT supplement survey and published by Jha et al.[14] We employed the classifications from Jha et al.'s study [14] to determine the necessity of certain individual functionalities to function as a basic electronic health record system, in order to classify each subsystems' adoption status.

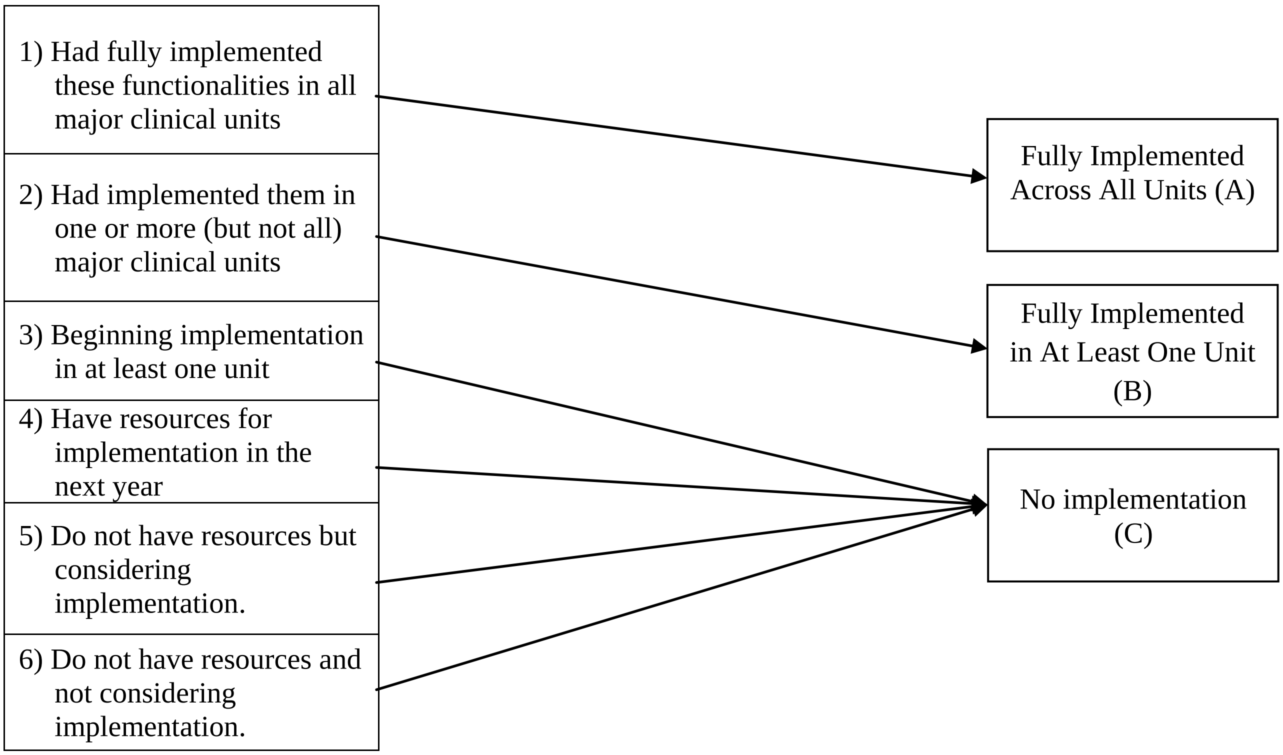


Figure 2. Classification for Status of Electronic Health Record Subsystem

Number of Electronic Health Record Subsystems

An ordinal scale variable was created by summing the five dichotomous subsystem-presence variables. The scale ranges from 0 to 5. In addition, five dichotomous variables (number of subsystems equals 1, number of subsystems equals 2, number of subsystems equals 3, number of subsystems equals 4, number of subsystems equals 5) were created to indicate the number of EHR subsystems that a hospital had adopted. For example, if a hospital adopted only one subsystem, then the variable "number of subsystems equals one" would be yes (coded as 1) and the other four variables would be no (coded as 0).

Status of Subsystem Adoptions

Five primary subsystems were of interest: computerized physician order entry, the decision support system, electronic clinical documentation, the barcode system, and the test result viewing system. According to the AHA EHR Survey, each of the five subsystems consists of several relevant functionalities. The subsystems and their associated functionalities are listed in Table 2. If all functionalities were fully implemented across all units (A), we categorized the status of electronic clinical documentation as "fully implemented across all units". We categorized the status as "fully implemented in at least one unit" if the relevant functionalities were fully implemented in one or more units, but not all (B). Hospitals which had any of the relevant functionalities not implemented (C) were classified as "not fully implemented yet."

[Table 2]

Table 2. Electronic Requirements for Classification of Hospitals as levels of Implementation for Electronic Clinical Documentation

	Across All Units	At Least One Unit But NOT All	No Implementation
Computerized Physician Order Entry			
Laboratory Tests	**A**	**A/B/C***	**B/C****
Radiology Tests	**A**	**A/B/C***	**B/C****
Medications	**A**	**A/B**	**C**
Consultation Requests	**A**	**A/B/C***	**B/C****
Nursing Orders	**A**	**A/B/C***	**B/C****
Decision Support System			
Clinical Guidelines	**A**	**A/B***	**Any of the Functionalities were not implemented.**
Clinical Reminders	**A**	**A/B***	
Drug Allergy Alerts	**A**	**A/B***	
Drug-Drug Interaction Alerts	**A**	**A/B***	
Drug-Lab Interaction Alerts	**A**	**A/B***	
Drug Dosing Support	**A**	**A/B***	
Electronic Clinical Documentation			
Patient Demographics	**A**	**A/B***	**Any of the Functionalities were not implemented.**
Physician Notes	**A**	**A/B***	
Nurse Notes	**A**	**A/B***	
Problem Lists	**A**	**A/B***	
Medication Lists	**A**	**A/B***	
Discharge Summaries	**A**	**A/B***	
Advanced Directives	**A**	**A/B/C***	**A/B/C**

Barcode System			
laboratory Specimens	**A**	**A/B***	**Any of the Functionalities were not implemented.**
Tracking Pharmaceuticals	**A**	**A/B***	
Pharmaceutical Administration	**A**	**A/B***	
Supply Chain Management	**A**	**A/B***	
Patient Identification	**A**	**A/B***	
Test Results Viewing System			
Lab Reports	**A**	**A/B***	**Any of the Functionalities were not implemented.**
Radiology Reports	**A**	**A/B***	
Diagnostic Test Results	**A**	**A/B***	
Radiology Images	**A**	**A/B/C***	**A/B/C**
Diagnostic Test Images	**A**	**A/B/C***	**A/B/C**
Consultant Reports	**A**	**A/B/C***	**A/B/C**

Note: A--defined as functionality in all clinical units
B--defined as functionality in at least one unit but not all
C--defined as functionality not implemented yet.
***Not simultaneously all equal to A.**
**** Not simultaneously all equal to B.**

Presence of Electronic Health Record Subsystems

In order to compare risk-adjusted mortality rates between hospitals that had one or more subsystems and those that did not, five dichotomous variables were created to indicate the presence of the primary subsystems (electronic clinical documentation, test results viewing system, decision support system, computerized physician order entry, and barcode system) in at least one unit of a hospital.

Additional Independent Variables

Hospital Characteristics

The hospital characteristics variables included in this analysis are shown in Table 3. Previous research indicates that these factors are associated with EHR adoption [18, 69, 70] or mortality rates of patients with AMI or CHF [59, 66, 71].

Table 3. Hospital Characteristics Description

Variable Name	Variable Type	Description
Hospital_Type	Categorical	It includes three categories: public, profit, or private.
Hospital_Location	Dichotomous	Urban or rural.

MemberofSystem	Dichotomous	It shows whether or not a hospital is a member of any hospital system
Hospital_Size	Categorical	Based on total hospital beds, a categorical variable was created to classify three levels of hospital size: small (6-99 beds), medium (100-399 beds), and large (more than 400 beds).
COTH	Dichotomous	Whether a hospital is a member of The Council of *Teaching* Hospitals and Health Systems
Cath_Lab	Dichotomous	Whether or not a hospital provides adult interventional cardiac catheterization
Transplant_Hospital	Dichotomous	Whether a hospital or its subsidiary provides heart transplants.
Emergency_Services	Dichotomous	Refers to the presence of an emergency department
Cardiac_Bed	Continuous	Total designated cardiac ICU beds
VEM	Continuous	Total outpatient emergency visits
FTE	Continuous	Total full time equivalent personnel

Statistic Analysis

Descriptive Statistics

Descriptive statistics and graphs were used to determine the distribution of five subsystem adoption statuses among hospitals, the distribution of risk-adjusted mortality rates (RSMRs), and the average RSMRs among hospitals that have implemented EHR systems in distinct subsystems.

Distribution of Subsystem Adoption Statuses among Hospitals

Across hospitals with different subsystems, continuous variables, such as hospital beds, total surgeries, total admissions and full time equivalent staff, were presented as means and compared using the Student's *t*-test or one way Analysis of Variance (ANOVA). Categorical variables, such as hospital location, profitability type, hospital size, and the presence of a cardiac catheterization lab, were presented as proportions and compared by Chi-square analysis.

Distribution of RSMRs among Hospitals

Among hospitals, we compared RSMRs for each year, from 2008 to 2009. Hospital characteristics, such as hospital size, with more than two levels were compared by one way ANOVAs; those with two levels, such as presence of heart transplant facilities, were compared by the Student's *t*-test.

Distribution of RSMRs among Each Subsystem's Adoption Statuses

We compared the RSMRs among hospitals with different adoption statuses for each of the five subsystems in 2008. To assess lagged effects, we examined the correlation between RSMRs and adoption statuses in 2009 as well.

Propensity Score Analysis

Because the study data are observational, there were pre-existing differences between hospitals that did and did not have an electronic health record system. For example, EHR adoptions may be more prevalent among low-mortality hospitals. This would cause cross-sectional regressions to overestimate the effect of EHR adoption on mortality rates. We therefore used a Probit model [Model 1] to estimate how likely a hospital was to adopt an electronic health record system in 2008, given hospital characteristics as predictors. We mitigated this potential source of selection bias by weighting propensity score in regression models. Thus, for a given propensity score, the likelihood of an electronic health record system adoption is random and hospitals with and without an electronic health record system should be, on average, observationally identical.

Model 1. Propensity Score Analysis for Hospitals with Electronic Health Record System

$$P(EHR\_Adoption = 1 \mid Hospital\_Characteristics_i) = (\text{Hospital\_Characteristics}_\text{i})$$

The quality of propensity score matching were assessed by computing the pseudo R-squares from regression models of the impact of electronic health record system adoption on hospital characteristics on the sample hospitals before and after weighting. Moreover, differences in major hospital characteristics between hospitals with and without EHR adoption were tested and shown no significance after propensity score weighting. [Table 4]

Table 4. Comparison of Hospital Characteristics between Hospitals with and without EHR before and after propensity score weighting

	Before Weighting			**After Weighting**		
	Adoption	No Adoption	P-value	Adoption	No Adoption	P-value
Hospital Size	2.00	1.78	0.000	1.99	2.01	0.573

Member of Hospital Systems	0.55	0.45	0.018	0.53	0.61	0.326
Full Time Equivalent Staffs	1576	948	0.000	1457	1395	0.312
Urban	0.93	0.78	0.000	0.93	0.92	0.931
Cardiac Catheterization Lab	0.53	0.37	0.000	0.53	0.51	0.443
Emergency Visits	0.40	0.28	0.000	0.39	0.40	0.664
Teaching Status	1.86	1.95	0.002	1.86	1.88	0.269
Hospital Profitability Type	1.94	1.91	0.525			
Heart Transplant Services	0.54	0.31	0.146			

Ordinary Least Squares (OLS)

Electronic Health Record Adoption vs. Risk-Adjusted Mortality Rates (RSMRs)

We analyzed outcomes for RSMRs of AMI and of CHF patients in 2009. For each of the four dependent variables, we compared two types of models: one with propensity score adjustment [Model 2] and one that controlled all relevant hospital characteristics without propensity score [Model 3].

Model 2

$RSMR_{AMI_{2009}} =$

$\beta_0 + \beta_1(EHR\_adoption\ _i) + \beta_2 \mathrm{P}\left(\mathrm{EHR}_{\mathrm{Adoption}} = 1 \,\middle|\mathrm{Hospital}_{\mathrm{Characteristics}_i}\right) + \varepsilon$

Where

EHR_adoption=whether the electronic health record system was in place before 2008

$\mathrm{P}\left(\mathrm{EHR}_{\mathrm{Adoption}} = 1 \,\middle|\mathrm{Hospital}_{\mathrm{Characteristics}_i}\right)$=propensity score from model 1

Model 3

$$RSMR_{AMI_{2009}} = \beta_0 + \beta_1(EHR\_adoption\ _i) + \beta_2(\mathrm{Hospital\_type}_i) + \beta_3(Hospital\_size\ _i)$$
$$+ \beta_4(\mathrm{Hospital\_location}_i) + \beta_5(\mathrm{Memberofsystem}_i)$$
$$+ +\beta_6(COTH) + \beta_7(Cat\square\_lab_i) + \beta_8(Transplant\_Hospital_i) + \beta_9(FTE_i)$$
$$+ \beta_{10}(VEM_i) + \varepsilon$$

Where

EHR_adoption=whether the electronic health record system was in place before 2008

Other variables= [See Table 3]

Number of Subsystems vs. Risk-Adjusted Mortality Rates

Besides analyzing the effect of an EHR system, we analyzed how the sequence of the implementation influences various treatment outcomes, using the number of subsystems as the primary endogenous variable. Model 5 was used to test the marginal effect of the number of adopted subsystems, while Model 6 was designed to determine the effect of different numbers of subsystems on outcomes when compared to hospitals with no implementation.

Model 5

$$RSMR_{AMI_{2009}} = \beta_0 + \beta_1(NumSystem) + \beta_2 \mathrm{P}\left(\mathrm{EHR_{Adoption}} = 1 \,\middle|\, \mathrm{Hospital_{Characteristics_i}}\right) + \varepsilon$$

Model 6

$$\begin{aligned} RSMR_{AMI_{2009}} = \beta_0 + \beta_1(NumSystem = 1) + \beta_2(NumSystem = 2) + \beta_3(NumSystem \\ = 3) + \beta_4(NumSystem = 4) + \beta_5(NumSystem \\ = 5) + \beta_1 \mathrm{P}\left(\mathrm{EHR_{Adoption}} = 1 \,\middle|\, \mathrm{Hospital_{Characteristics_i}}\right) + \varepsilon \end{aligned}$$

Where

NumSystem=how many subsystems out of five had been adopted in 2008

NumSystem=i = whether a total of i subsystems were adopted in at least one unit of a hospital

$P(EHR\_Adoption = 1 \mid Hospital\_C\square aracteristics_i)$=propensity score from model 1

Presence of Subsystems vs. Risk-Adjusted Mortality Rates

Further, we created a different model to estimate how each of the subsystems impacted RSMRs both in 2008 and in 2009. For this purpose, the first part of the analysis employed five dichotomous variables (defined as whether each subsystem was fully adopted in at least one unit) as primary independent variables. [Model 4]

Model 4

$$RSMR_{AMI_{2009}} = \beta_0 + \beta_1(ECD_{\ i}) + \beta_2(LR_{\ i}) + \beta_3(CPOE_{\ i}) + \beta_4(DS_{\ i}) + \beta_5(Barcode_i) + \beta_6\, \mathrm{P}\big(EHR_{Adoption} = 1\,\big|Hospital_{C\square aracteristics_i}\big) + \varepsilon$$

Where *ECD*=whether electronic clinical documentation was in place

LR=whether a test results viewing system was in place

CPOE=whether computerized physician order entry was in place

DS=whether a decision support system was in place

Barcode=whether a barcode system was in place

$P(EHR\_Adoption = 1\,|Hospital\_C\square aracteristics_i)$=propensity score from model 1

Statuses of Subsystems vs. Risk-Adjusted Mortality Rates

The following five linear regression models [Model 7-Model 11] were developed using each subsystem's different adoption statuses as primary independent variables (i.e. adoption across all units and adoption in at least one unit), using no implementation of each subsystem as a reference, while controlling for the presence of other subsystems in the model. We list AMI models as examples since heart failure models are the same.

Model 7

$$RSMR_{AMI_{2009}} = \beta_0 + \boldsymbol{\beta_1(ECD\_all_i)} + \boldsymbol{\beta_2(ECD\_one_i)} + \boldsymbol{\beta_3}(LR_{\ i}) + \beta_4(CPOE_{\ i}) + \beta_5(DS_{\ i}) + \beta_6(Barcode_i) + \beta_7\mathrm{P}\big(\mathrm{EHR_{Adoption}} = 1\,\big|\mathrm{Hospital_{Characteristics_i}}\big) + \varepsilon$$

Model 8

$$RSMR_{AMI_{2009}} = \beta_0 + \boldsymbol{\beta_1(LR\_all_i)} + \boldsymbol{\beta_2(LR\_one_i)} + \beta_3(ECD_{\ i}) + \beta_4(CPOE_{\ i}) + \beta_5(DS_{\ i}) + \beta_6(Barcode_i) + \beta_7\mathrm{P}\big(\mathrm{EHR_{Adoption}} = 1\,\big|\mathrm{Hospital_{Characteristics_i}}\big) + \varepsilon$$

Model 9

$$RSMR_{AMI_{2009}} = \beta_0 + \boldsymbol{\beta_1(CPOE\_all_i)} + \boldsymbol{\beta_2(CPOE\_one_i)} + \beta_3(LR_{\ i}) + \beta_4(ECD_{\ i}) + \beta_5(DS_{\ i}) + \beta_6(Barcode_i) + \beta_7\mathrm{P}\big(\mathrm{EHR_{Adoption}} = 1\,\big|\mathrm{Hospital_{Characteristics_i}}\big) + \varepsilon$$

Model 10

$$RSMR_{AMI_{2009}} = \beta_0 + \boldsymbol{\beta_1}(\boldsymbol{DS\_all_i}) + \boldsymbol{\beta_2}(\boldsymbol{DS\_one_i}) + \beta_3(LR\ _i) + \beta_4(CPOE\ _i) + \beta_5(ECD\ _i)$$
$$+ \beta_6(Barcode_i) + \ \beta_7 \mathrm{P}\big(\mathrm{EHR_{Adoption}} =\ 1\ \big|\mathrm{Hospital_{Characteristics_i}}\big) + \varepsilon$$

Model 11

$$RSMR_{AMI_{2009}} = \beta_0 + \boldsymbol{\beta_1}(\boldsymbol{Barcode\_all_i}) + \boldsymbol{\beta_2}(\boldsymbol{Barcode\_one_i}) + \beta_3(LR\ _i) + \beta_4(CPOE\ _i)$$
$$+ \beta_5(DS\ _i) + \beta_6(ECD_i) + \ \beta_7 \mathrm{P}\big(\mathrm{EHR_{Adoption}} =\ 1\ \big|\mathrm{Hospital_{Characteristics_i}}\big) + \varepsilon$$

Where

X_all=whether subsystem X was implemented across all units

X_one=whether subsystem X was implemented in at least one unit

ECD=whether electronic clinical documentation system was in place

LR=whether a test results viewing system was in place

CPOE=whether computerized physician order entry was in place

DS=whether a decision support system was in place

Barcode=whether a barcode system was in place

$P(EHR\_Adoption =\ 1\ |Hospital\_C\square aracteristics_i)$=propensity score from model 1

The models were tested in several ways for specification. The Ramsey Regression Equation Specification Error Test [72] was used to determine if there was any incorrect exclusion of a relevant independent variable from the model; or if the model has any misspecification, such as inclusion of irrelevant variables or faulty functional forms. Lastly, we utilized the variance inflation factor (VIF) method and the White test for multicollinearity and heteroskedasticity, respectively.

All statistical analyses were conducted using STATA 11 (StataCorp LP, College Station, TX); all data formatting were performed in SAS 9.2 (SAS Institute, Cary, NC).

RESULTS

Descriptive Statistics

The sample is comprised of approximately 19% of U.S hospitals, accounting for approximately 26% of the hospital beds in the U.S. As shown in Table 5, sample hospitals are generally large, located in urban areas, and provide cardiac catheterization laboratories. 18% of the sample hospitals have more than 400 staffed beds, but these hospitals account for 35% of large hospitals in the United States. Also, the 5% of sample hospitals providing heart transplants account for 35% of hospitals with heart transplant services in the United States. Of the sample hospitals, 53% are members of healthcare systems, and 76% are private and nonprofit. Additionally, the average hospital beds and cardiac beds per hospital are much more than the normative levels in the U.S.

Table 5. Share of Sample Hospitals in the United States (2008)

	Number (Sample %)	U.S. %
Number of Hospitals	969 (100%)	19%
Member of a system	512 (53%)	15%
Teaching Hospital	124 (13%)	10%
Total Hospital Beds, Thousand	252 (100%)	26%
Hospital Type		
Public [a]	147 (15%)	10%
Private, not-for-profit [b]	738 (76%)	23%
For-Profit [c]	84 (9%)	6%
Urban	881 (91%)	24%
Hospital Size		
Small (6-99 beds)	209 (22%)	6%
Medium (100-399 beds)	584 (60%)	23%
Large (>=400 beds)	176 (18%)	35%
Total Cardiac Beds (hundred)	58 (100%)	29%
Heart Transplant Service	47 (5%)	35%
Cardiac Catheterization Laboratory	491 (51%)	36%
Hospital Beds (thousand), Mean(SD)	260 (222)	153 (179)
Cardiac Bed Size Per Hospital, Mean(SD)	6 (9.32)	3 (7.3)

Note. In 2008, there were 5,008 nonfederal, short-term hospitals in the U.S.
a. Public hospitals-government, nonfederal hospitals.
b. Private hospitals-nongovernment, not-for-profit hospitals operated by churches or other not-for-

profit institutions
c. For-Profit hospitals-investor-owned, for profit hospitals.

Adoption of Electronic Health Record Subsystems

Within the sample, 37% of the hospitals had adopted computerized physician order entry, but only 16% had full adoption across all clinic units. A laboratory/radiology test results viewing system was the most popularly implemented among the five subsystems. Only 13% of hospitals had not adopted a test results viewing system in 2008. [Appendix. Table 6]

The statuses of EHR subsystem adoption significantly differ by hospital characteristics. Large hospitals (defined as having more than 400 staffed beds), urban hospitals, hospitals with a membership of health systems, teaching hospitals, hospitals with cardiac catheterization laboratories, and hospitals with larger nurse staffing ratios tend to have full adoption across all clinic units.

Hospitals with more staffed beds had a higher proportion of adoption of all five subsystems ($p<0.003$) [Appendix Table 12a-Table 12e]. Approximately 91% of large hospitals had adopted any EHR subsystem. However, while 38% of large hospitals had fully adopted computerized physician order entry, only 8% of small hospitals had adopted this subsystem across all units [Table 6].

Furthermore, adoption statuses among different hospital profitability types show significant differences only with respect to the adoption of electronic clinical documentation and test results viewing systems [Appendix. Table 12a, Table 12e]. Public hospitals have the highest percentage of electronic clinic documentation adoption across all units, but also have the highest percentage of no implementation among the different profitability types. In contrast, for-profit hospitals and private nonprofit hospitals have a higher percentage of electronic clinic documentation adoption in at least one unit than public hospitals. Among different hospital types, private nonprofit hospitals generally had the highest percentage of full adoption across all units in terms of computerized physician order entry, decision support systems and test results viewing systems [Table 6].

Hospitals belonging to a hospital system consistently had higher percentages of full adoption of all five subsystems. Approximately 88% of membership-owned hospitals had at least one subsystem in place, generally a test results viewing system. Still, among hospitals with membership of a hospital system, only 20% of them had full adoption of computerized physician order entry and just 13% of them had fully adopted electronic clinical documentation.

Teaching hospital status plays an important role on the progress of adoption for all of the subsystems, except for the barcode system. Hospitals with barcode system adoption across all units were overwhelmingly located in urban settings. Merely 2% of rural hospitals had full barcode system adoption across all clinic units. With respect to the test results viewing system, in 2008, only 8% of teaching hospitals had no implementation, whereas 14% of non-teaching hospitals were without a test results viewing system. Notably, teaching hospitals had more than twice the full adoption rate of computerized physician order entry, decision support system and electronic clinical documentation subsystems than non-teaching hospitals [Table 6].

Like teaching status, proximity to an urban area had significant effects on the adoption status of the subsystems. For all five subsystems, urban hospitals had more than twice the levels of full adoption than rural hospitals. 17% of urban hospitals had adopted computerized physician order entry across all units, compared to adoption for only 5% of rural hospitals. Additionally, whereas only 11% of urban hospitals had not adopted a test results viewing subsystem, 32% of rural hospitals had no implementation of this subsystem. [Table 6]

Subsystem Adoption vs. Risk-Adjusted Mortality Rates

Table 7 depicts the AMI and CHF risk-adjusted mortality rates among hospitals with various subsystem adoption statuses. With the exception of barcode systems, hospitals with adoption of subsystems across all units had significantly lower mortality rates ($p<0.0289$). The adoption of barcode systems resulted in practical reduction in the CHF mortality rates. From 2008 to 2009, average AMI mortality rates have reduced while CHF mortality rates have increased [Table 7].

Table 7. Cardiac Risk-Adjusted Mortality Rates by Electronic Health Record Functionality and Year

	Risk-Adjusted Mortality Rates (SD)			
	Acute Myocardial Infarction		Congestive Heart Failure	
	2008	2009	2008	2009
Presence of Functionality				
Computerized Physician Order Entry				
Yes (N=360)	15.95 (1.74)	15.78 (1.23)	10.70 (1.73)	10.76 (1.74)
No (N=609)	16.55 (1.80)	16.15 (1.17)	11.04 (1.64)	11.21 (1.59)
Δ (No-Yes), Mean (95% CI)	0.60 (0.37-0.83)	0.37 (0.22-0.53)	0.33 (0.11-0.55)	0.45 (0.23-0.66)
P-Value for difference	<0.0001	<0.0001	0.0015	<0.0001
Decision Support System				
Yes (N=552)	16.08 (1.79)	15.83 (1.22)	10.78 (1.68)	10.94 (1.72)
No (N=417)	16.65 (1.76)	16.25 (1.16)	11.09 (1.67)	11.17 (1.57)
Δ (No-Yes), Mean (95% CI)	0.56 (0.34-0.79)	0.41 (0.26-0.56)	0.31 (0.10-0.53)	0.23 (0.02-0.44)
P-Value for difference	<0.0001	<0.0001	0.0021	0.0156
Barcode System				
Yes (N=568)	16.23 (1.75)	15.94 (1.17)	10.89 (1.67)	11.02 (1.66)
No (N=401)	16.46 (1.87(	16.12 (1.26)	10.95 (1.70)	11.06 (1.66)
Δ (No-Yes), Mean (95% CI)	0.22 (-0.01-0.45)	0.18 (0.02-0.33)	0.06 (-0.16-0.27)	0.05 (-0.17-0.26)
P-Value for difference	0.0289	0.0129	0.2971	0.3374
Electronic Clinic Documentation Adoption				
Yes (N=609)	16.21 (1.80)	15.92 (1.23)	10.83 (1.66)	10.93 (1.61)
No (N=360)	16.51 (1.78)	16.17 (1.17)	11.06 (1.71)	11.21 (1.73)
Δ (No-Yes), Mean (95% CI)	0.29 (0.06-0.53)	0.24 (0.09-0.40)	0.23 (0.01-0.45)	0.28 (0.06-0.50)
P-Value for difference	0.0072	0.0013	0.0185	0.0056
Laboratory/Radiology Test Review System				
Yes (N=841)	16.25 (1.80)	15.97 (1.23)	10.87 (1.68)	10.99 (1.68)
No (N=128)	16.86 (1.73)	16.30 (1.04)	11.18 (1.65)	11.30 (1.51)
Δ (No-Yes), Mean (95% CI)	0.61 (0.28-0.94)	0.32 (0.10-0.55)	0.30 (-0.01-0.62)	0.31 (-0.00-0.62)
P-Value for difference	0.0002	0.0025	0.0287	0.0256

Hospital Characteristics vs. Risk-Adjusted Mortality Rates

In our study sample, the AMI risk-adjusted mortality rates were approximately 16%; and 11% for CHF. Having found significant differences between hospital profitability type

($p<0.0001$), urban/rural location ($p<0.0001$), membership in a hospital system ($p<0.0493$), hospital size ($p<0.0001$), heart transparent services ($p<0.0013$), teaching status ($p<0.0001$), and presence of cardiac catheterization laboratory ($p<0.0001$), the average risk adjusted mortality rates are also significantly different ($p<0.005$) [Table 8]. The differences in the hospital characteristics are significantly associated with the difference in the average risk adjusted mortality rates ($p<0.0493$) [Table 8].

Table 8. Condition-Specific Risk-Adjusted Mortality Rates from 2007 to 2009 by Hospital Characteristics

	Risk-Adjusted Mortality Rates, Mean (SD)					
	Acute Myocardial Infarction			Heart Failure		
	2007	2008	2009	2007	2008	2009
Hospital Profitability Type						
Public	16.26 (0.82)	16.90 (1.82)	16.62 (1.74)	11.23 (1.04)	11.44 (1.48)	11.56 (1.46)
Profit	16.18 (0.96)	16.81 (1.79)	16.45 (1.72)	11.17 (1.24)	11.12 (1.51)	11.26 (1.50)
Private	16.05 (1.09)	16.34 (1.79)	16.00 (1.70)	11.06 (1.31)	11.10 (1.59)	11.23 (1.59)
P-Value for difference	<0.0001	<0.0001	<0.0001	0.0023	<0.0001	<0.0001
Hospital Location						
Urban	16.07 (1.16)	16.36 (1.80)	16.07 (1.75)	11.05 (1.37)	11.02 (1.61)	11.15 (1.62)
Rural	16.20 (0.59)	17.09 (1.54)	16.67 (1.33)	11.23 (0.93)	11.50 (1.39)	11.66 (1.36)
P-Value for difference	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Member of Hospital System						
Yes	16.08 (1.05)	16.41 (1.78)	16.10 (1.70)	11.07 (1.28)	11.06 (1.55)	11.20 (1.56)
No	16.15 (1.00)	16.60 (1.84)	16.25 (1.75)	11.16 (1.20)	11.31 (1.56)	11.42 (1.56)
P-Value for difference	0.033	0.0112	0.0322	0.0493	<0.0001	<0.0001
Hospital Size						
Small (6-99 beds)	16.18 (0.67)	16.88 (1.58)	16.53 (1.46)	11.24 (0.96)	11.46 (1.40)	11.61 (1.38)
Medium (100-399 beds)	16.10 (1.12)	16.47 (1.79)	16.17 (1.72)	11.09 (1.39)	11.06 (1.62)	11.18 (1.63)
Large (>=400 beds)	15.88 (1.56)	15.90 (2.03)	15.59 (1.94)	10.68 (1.49)	10.56 (1.64)	10.68 (1.62)
P-Value for difference	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Heart Transplant Services						
Yes	15.70 (1.25)	15.65 (1.81)	15.31 (1.80)	10.23 (1.33)	10.14 (1.54)	10.34 (1.55)
No	16.12 (1.02)	16.53 (1.80)	16.20 (1.71)	11.14 (1.23)	11.20 (1.55)	11.33 (1.55)
P-Value for difference	0.0013	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Teaching Status						
Yes (N=124)	15.31 (2.00)	15.54 (2.06)	15,61 (1.54)	10.27 (1.37)	10.10 (1.56)	10.24 (1.47)
No (N=823)	16.11 (1.66)	16.44 (1.73)	16.08 (1.12)	11.10 (1.42)	11.03 (1.66)	11.15 (1.52)
P-Value for difference	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Cardiac Catheterization Lab						
Yes	15.93 (1.35)	16.12 (1.9)	15.83 (1.81)	10.92 (1.47)	10.86 (1.67)	11.00 (1.69)
No	16.19 (0.83)	16.77 (1.68)	16.42 (1.61)	11.19 (1.13)	11.32 (1.49)	11.44 (1.47)
P-Value for difference	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001

Propensity Score Analysis

The significant differences of risk adjusted mortality rates reflect the preliminary differences among hospitals with different EHR adoption. For example, an EHR adoption may be more prevalent among low-mortality hospitals. Employing propensity score analysis, urban hospitals and hospitals with more emergency visits were found to significantly predict the presence of EHR adoption ($p<0.0001$ and $p=0.07$, respectively). Given the predictors in Table 9, the probability of EHR adoption in 2008 among the sample is 84.8 ± 8%. Given the inverse probability weights of an EHR adoption, insignificant differences of the hospital characteristics are shown ($p>0.269$) in Table 9b.

Table 9. Propensity Score Analysis for Probability of Electronic Health Records Adoption in 2008

	β (SE)	**p-value**
Hospital Size	-0.14 (0.13)	0.309
Member of Hospital Systems	0.02 (0.10)	0.874
Full Time Equivalence	0.96 (0.99)	0.333
Urban	0.64 (0.17)	0.000 ***
Cardiac Catheterization Lab	0.03 (0.13)	0.832
Emergency Visits	4.62 (3.94)	0.070 *
Teaching Status	-0.13 (0.25)	0.596
Nurse Staff Ratio	0.15 (0.12)	0.215

Notes: Number of observations=969

- Pseudo R2=0.0610
- Predicted Probability of electronic health records adoption in 2008=0.848 with standard deviation=0.08
- Average inverse probability weights=2.04

Table 9b. Impact of Propensity Score Weighting on Differences of Hospital Characteristics

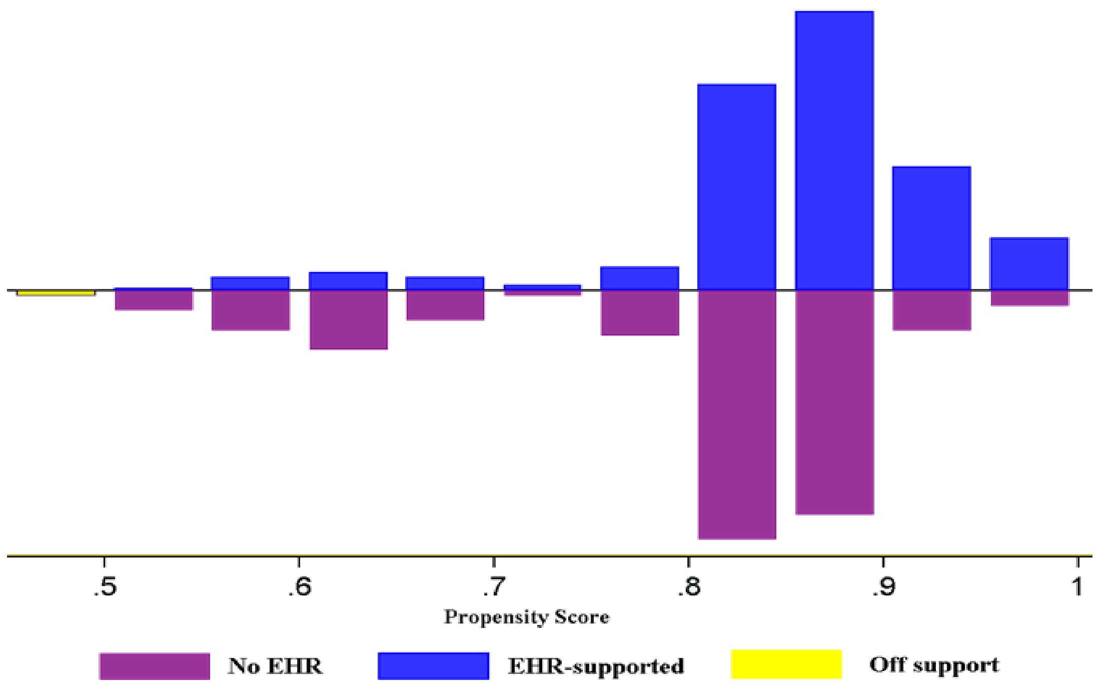
	Before Weighting			**After Weighting**		
	Adoption	No Adoption	P-value	Adoption	No Adoption	P-value
Hospital Size	2.00	1.78	0.000	1.99	2.01	0.573
Member of Hospital Systems	0.55	0.45	0.018	0.53	0.61	0.326
Full Time Equivalent Staffs	1576	948	0.000	1457	1395	0.312
Urban	0.93	0.78	0.000	0.93	0.92	0.931
Cardiac Catheterization Lab	0.53	0.37	0.000	0.53	0.51	0.443
Emergency Visits	0.40	0.28	0.000	0.39	0.40	0.664
Teaching Status	1.86	1.95	0.002	1.86	1.88	0.269

Hospital Profitability Type	1.94	1.91	0.525	
Heart Transplant Services	0.54	0.31	0.146	

The other assumption for the propensity score analysis is to have enough rate of overlapping between two groups- see figure 3; the bottom-half of each graph shows the propensity score distribution for the non-adopted, while the upper-half refers to the hospitals with an EHR.

Among hospitals who adopted an EHR in 2008, the predicted propensity score ranges from 0.52 to 0.99 with a mean of 0.86. Among non-implemented hospitals, the predicted propensity score ranges from 0.47 to 0.98 with a mean of 0.79. Thus, the common support assumption is satisfied in the region of [0.52, 0.98] enforcing a loss of 14 shocked hospitals. The density distributions of the propensity scores [Figure 3] also support the common support or overlap region for adopted and non-adopted hospitals.

Figure 3. Density distribution of propensity scores



Ordinal Least Squares Regression

Five series of ordinary least squares regression models were conducted, using AMI and CHF risk adjusted mortality rates as the dependent variables. Primary independent variables are 1) the presence of EHR, 2) the number of subsystems (ordinal), 3) the categorized number of subsystems, 4) the presence of subsystems, and 5) the adoption status of subsystems. Models incorporated the predicted probability of electronic health record system adoption to determine whether confounding factors are significantly contributing to RSMRs, after adjustment for selection bias. Table 10 displays the results of the models.

Presence of Electronic Health Record System

The first model was used to determine the relationship between AMI or CHF risk-adjusted mortality rates and the presence of an EHR. The results support our initial hypothesis that EHR adoption is significantly associated with a lower RSMR (p=0.015). The negative sign indicates that as hospitals adopted EHR, their mortality rates decrease by as much as 0.59% [Table 10].

Table 10. Adjusted Effects of EHR Subsystem Adoption on Cardiac Risk-Adjusted Mortality Rates (%) in 2009

Acute Myocardial Infarction						
β (SE) **Variables**	Model 1. Presence of Electronic Health Records	Model 2. Number of Subsystems	Model 3. Number of Subsystems vs. no subsystem	Model 4. Presence of Subsystems	Model 5. Subsystem Adoption Status Across All Units	 At Least One Unit
Presence of Electronic Health Records	**-0.59 (0.21)***					
Number of Subsystems		**-0.24 (0.04)***				
Number of Subsystems (Ref. no implementation)						
1			0.05 (0.31)			
2			-0.32 (0.28)			
3			**-0.62 (0.27)**			
4			**-0.74 (0.27)***			
5			**-1.09 (0.28)***			
Presence of Subsystems						
CPOE [a]				**-0.63 (0.19)***	**-0.81 (0.19)***	**-0.52 (0.25)**
Decision Support				-0.25 (0.19)	**-0.44 (0.24)***	-0.16 (0.20)
ECD [b]				-0.04 (0.17)	-0.14 (0.25)	-0.01 (0.17)
Barcode				-0.15 (0.15)	-0.02 (0.23)	-0.15 (0.15)
Test Results Viewing				-0.07 (0.28)	-0.19 (0.33)	-0.05 (0.27)
R Squares for Models	2.56%	3.50%	3.65%	4.34%	4.79%	

Congestive Heart Failure						
Presence of Electronic Health Records	**-0.35 (0.17)****					
Number of Subsystems		**-0.13 (0.04)*****				
Number of Subsystems (Ref. no implementation)						
1			0.16 (0.29)			
2			-0.29 (0.25)			
3			-0.24 (0.25)			
4			-0.28 (0.25)			
5			**-0.68 (0.26)*****			
Presence of Subsystems						
CPOE [a]				**-0.38 (0.13)*****	**-0.72 (0.19)*****	-0.23 (0.18)
Decision Support				-0.01 (0.17)	-0.23 (0.23)	-0.13 (0.18)
ECD [b]				-0.18 (0.17)	0.31 (0.26)	0.003 (0.18)
Barcode System				-0.05 (0.15)	-0.03 (0.19)	-0.06 (0.16)
Test Results Viewing				0.05 (0.24)	-0.02 (0.32)	0.09 (0.24)
R Squares for Models	1.08%	1.20%	1.74%	1.63%	2.22%	

Note: Models were weighted by propensity scores; * p<0.1 **p<0.05 ***p<0.01

a. CPOE-Computerized Physician Order Entry
b. ECD-Electronic Clinic Documentation

Number of Electronic Health Record subsystems

The second series of OLS models were analyzed to determine if the number of EHR subsystems is associated with changes in AMI or CHF RSMRs. The results of these OLS models consistently support our initial hypothesis that an increased number of electronic health record subsystems is significantly associated with lower RSMRs ($p<.0001$ for AMI models; $p<0.057$ for CHF models). A negative sign on the number of subsystems variable indicates that with an additional subsystem adoption, RSMRs decrease by 0.24% of AMI RSMRs and 0.13% of CHF RSMRs. That is, adopting one more subsystem might reduce 24 and 13 deaths per 10,000 AMI and CHF patients, respectively. [Table 10]

Of particular interest, the third series of OLS models were conducted to assess how the adoption of specific numbers of subsystems influence AMI or CHF RSMRs, compared with no adoption. As expected, additional subsystems resulted in additional decreases in RSMRs. Optimal results were achieved for AMI when hospitals fully adopted at least 3 subsystems; for CHF, results were optimal when a hospital had adopted all 5 subsystems. [Table 10. Model 3]

Electronic Health Record Subsystems - Without controlling for other subsystems' presence

Results from the unadjusted OLS regression of correlates of each cardiac RSMRs following different subsystems' adoption are displayed in Table 11. There are four series of models with different types of independent variables (presence of each subsystem adoption and status of each subsystem adoption) and two cardiac conditions, without controlling for the presence of other subsystems.

Table 11. Unadjusted Effects of Electronic Health Record Subsystem Adoption on Cardiac Risk-Adjusted Mortality Rates in 2008

	Acute Myocardial Infarction, β (SE)			Heart Failure, β (SE)		
	Model 6 *i* [a]	Model 7 *i* [b]		Model 8 *i* [a]	Model 9 *i* [b]	
	Presence of Subsystem	**Across All Units** [c]	**At Least One Unit** [d]	**Presence of Subsystem**	**Across All Units** [c]	**At Least One Unit** [d]
Computerized Physician Order Entry	-0.80 (0.16)***	-1.12 (0.18)***	-0.62 (0.21)***	-0.46 (0.14)***	-0.78 (0.1)***	-0.27 (0.17)
Decision Support System	-0.58 (0.18)***	-0.85 (0.21)***	-0.44 (0.19)**	-0.32 (0.15)**	-0.51 (0.19)***	-0.25 (0.16)
Electronic Clinical Documentation	-0.37 (0.19)**	-0.72 (0.23)***	-0.30 (0.19)	-0.18 (0.16)	-0.28 (0.21)	-0.16 (0.17)
Barcode System	-0.42 (0.18)**	-0.52 (0.24)**	-0.40 (0.18)**	-0.20 (0.15)	-0.28 (0.19)	-0.18 (0.16)
Lab/Radiology Test Results Viewing System	-0.33 (0.26)	-0.53 (0.28)*	-0.18 (0.28)	-0.10 (0.19)	-0.23 (0.23)	-0.01 (0.21)

Notes: Models are weighted electronic health record adoption propensity score from propensity score analysis, but not controlled for the presence of other subsystems
*** p < .1 ** p < .05 *** p < .01**
a. Only consider whether each subsystem was in place in 2008, regardless of the adoption status
b. Models used "no implementation" as reference.
c. Full adoption across all units in a hospital
d. Full adoption in at least one unit but not all in a hospital

We first assessed five models [Model 6*i*] to determine if each subsystem significantly impacted RSMRs in 2009, regardless of the presence of other subsystems. Most subsystems significantly reduced

AMI RSMRs, except for test result viewing systems, which only significantly reduced AMI RSMRs when adopted across all units in a hospital. We also found that hospitals with adoption across all units have higher magnitudes of RSMR reduction than hospitals with only partial adoption [Table 11, Model 7*i*].

In terms of CHF, only computerized physician order entry and the decision order entry subsystems significantly contributed to the RSMR reduction when considering just the presence of the subsystem. In terms of adoption statuses, however, computerized physician order entry and decision support systems all led to significant reductions of CHF RSMRs only when they were adopted across all units.

The subsystem with the greatest effect once fully adopted was computerized physician order entry ($p<0.0001$). Hospitals with fully adopted computerized physician order entry had 0.80% lower AMI RSMRs. This indicates that computerized physician order entry adoption would reduce 80 deaths out of 10,000 AMI patients. Notably, with computerized physician order entry adoption across all units, hospitals would prevent as many as 112 deaths per 10,000 AMI patients, compared with those hospitals without the computerized physician order entry in place. [Table 11]

<u>Adjusted Models for Electronic Health Record Subsystems</u> -Controlling for the presence of other subsystems

We tested whether subsystems still had an impact on RSMRs in the presence of other subsystems. Table 10 depicts the results of these models. Similar to unadjusted models, only computerized physician order entry leads to significant reduction on both AMI and CHF RSMRs ($p<0.0001$). However, none of subsystems significantly reduced CHF RSMRs when not fully adopted across all units in a hospital [Table 10. Model 5]. The decision support system only had effects on AMI RSMRs as adopted across all units of a hospital, not on CHF RSMRs. With a computerized physician order entry adoption, hospitals would save 63 deaths per 10,000 AMI patients ($p<0.0001$) and 38 deaths per 10,000 CHF patients ($p=0.002$).

When a computerized physician order entry was adopted across all units in a hospital, 81 fewer deaths ($p<0.0001$) and 72 fewer deaths ($p<0.0001$) out of 10,000 patients with AMI and CHF, respectively, would take place [Table 10].

DISCUSSION

Summary

The adoption status of electronic health record (EHR) subsystems varies by hospital characteristics. Small hospitals, for-profit hospitals, hospitals not in a health care system, non-teaching hospitals, rural hospitals, and hospitals with a low nurse-to-patient ratio consistently demonstrated slow progress on adoption of all five EHR subsystems. After adjusting for major hospital characteristics, we found that hospitals with EHR adoption in at least one unit had a reduction of approximately 59 and 35 deaths per 10,000 acute myocardial infarction (AMI) and congestive heart failure (CHF) patients, respectively. Hospitals with at least 3 subsystems had significant reduction on AMI mortality rates, while only hospitals with all 5 subsystems had optimal results on CHF mortality rates. With respect to the effects of the presence of various subsystems, computerized physician order entry is the most significant EHR functionality with the decrease by as much as 0.81% on risk-adjusted mortality rates.

Study Implications

Electronic Health Record Adoption among Hospitals

The results suggest that significant variation exists in the implementation of EHR subsystems across U.S. hospitals. Being able to identify those hospital characteristics, which significantly contribute to distinct adoption statuses of EHRs, is crucial to national coordinators trying to determine how to award funds promulgated by the HITECH Act when implementing nationwide health information technology in the U.S. Previous research indicates larger hospitals, those located in urban areas, those with higher nursing staffing levels, higher full time equivalence, and teaching hospitals are more likely to have EHRs.[14, 18, 73] Our analysis supports these findings; however, the results of descriptive statistics in this study further suggest that there are other predictors of the EHR subsystem adoption, such as hospital profitability types, the membership of a hospital system, and number of emergency visits.

Presence of EHR and RSMRs

Our findings that the presence of an EHR in a hospital resulted in significant reductions in both AMI and CHF RSMRs are consistent with most existing studies. Accordingly, the improvement in hospital-wide mortality rates can likely be attributed to standardization of all medical records, consistency in hospitalized care, better communication among staff, and the fact that orders, vital-sign documentation, and prescription data become remotely accessible in time. Specifically, the benefit of EHR adoption is plausible since the most common cause of the cardiac mortality rates is known to be medication-administration delay [74], and EHR is shown to help accelerate the workflow efficiency [75].

As previously noted, not all existing literature supports EHR implementation. [45, 47, 76-80] Most of these non-supportive studies were either small case studies or focused on a specific subsystem. Few used nationally representative datasets. Our results add important information to the debate by providing evidence as follows: first, the number of adopted EHR subsystems overwhelms the benefits of how an EHR impacts on outcomes. Second, adoption of most EHR subsystems did not show significant impact on outcomes immediately. Third, the adoption status of a subsystem affects the effectiveness of an EHR on mortality rates. Moreover, even for two cardiac conditions, EHRs showed very different results with respect to the effects on the outcomes.

Number of Subsystems vs. Risk-Adjusted Mortality Rates

The effectiveness of EHR implementation is dependent on how many and what systems are adopted. We observed that only when hospitals fully adopted at least 3 subsystems were AMI deaths decreased by 62 out of 10,000 patients; this increased to 109 fewer deaths if all 5 subsystems were fully adopted in at least one unit. For CHF, not until a hospital fully adopted all 5 subsystems in at least one unit did EHRs significantly impact mortality rates. This phenomenon can be explained by the different clinical procedures between AMI and CHF as well as the complex nature of health care environments. Regarding clinical conditions between AMI and CHF, previous studies have shown that there is greater standardization of AMI protocols to assist the physician in making appropriate treatment and disposition decisions.[81, 82, 83, 84] Thus, AMI treatment may be more amenable to EHR adoption than CHF treatment.

In addition to the clinical conditions, health care environments also benefit from more subsystems- namely that the number of subsystems affects the effectiveness of an EHR adoption. Hospital personnel might initially suffer from EHR initiation while adopting the first several subsystems. And, it is possible that having more than 3 subsystems in place helps clinicians, nurses, pharmacists and administrators recognize critical mistakes such as side effects, incorrect dosages, inappropriate frequency, and mismatching patients, among others. Further, integration of health care workflow by multiple subsystem adoption should identify practices systematically, reduce medical errors or malpractice, and increase patient-interaction time for both AMI and CHF patients. Another possibility is that health care providers in hospitals with more subsystems have acclimated to a computer-based environment and been trained to use the computerized programs.

Effects of Subsystems Adoption vs. Risk-Adjusted Mortality Rates

To be specific, another finding of this study is that among five primary EHR subsystems, computerized physician order entry was the only significant one in the impact of both AMI (-0.63%; $p<0.001$) and CHF (-0.38%; $p<0.001$) mortality rates, but there were significant differences in mean mortality rates between an adoption and no adoption of a decision support system and electronic clinical documentation.

Adoption Status of Subsystems vs. Risk-Adjusted Mortality Rates

Rather than the presence of five subsystems, we found that the more hospitals' units that have fully adopted a subsystem, the higher the effects of the EHR adoption on mortalities would be. For example, despite the fact that the presence of computerized physician order entry consistently showed negative association with AMI and CHF mortality rates, full adoption of computerized physician order entry across all units would reduce more AMI mortalities (-0.81%) than in those hospitals with adoption in at least one unit but not all (-0.52%).

When it comes to CHF, computerized physician order entry demonstrated a significant impact on the mortality rates when computerized physician order entry was fully adopted across all units of a hospital, but no significance was demonstrated when computerized physician order entry was adopted partially. The clinical benefits from computerized physician order entry adoption have been widely-documented.[85-91] Computerized physician order entry facilitates decision support at the point of care and eliminates redundant procedures by health care providers, which improves accuracy and efficiency systematically. Therefore, it is not unexpected that computerized physician order entry is shown to be the most significant subsystem, but few hospitals (37%) currently have computerized physician order entry in place, and only 16% of those hospitals have fully adopted computerized physician order entry across all units, which we suggest is necessary to see effective results.

Limitations

This study does face some limitations, the most important of which is omitted variable bias. This study only considered whether or not a hospital has an EHR. Potential omitted variables include, for example, the number of health care providers who are effectively using distinct subsystems, the fitness of an EHR to a hospital, the vendors of an EHR in a hospital, and the length of time each subsystem had been adopted.

First, although EHRs are known to facilitate providers' decisions, the benefits of such technologies may be overstated due to the fact that some providers may have difficulty adjusting to a computerized workflow. Additionally, the variability in quality and exchangeability of EHR vendors may cause the impact of EHRs on mortality to be overstated. Finally, the length of time since EHR implementation was not accounted for; a shorter average length of time since implementation can result in the underestimated EHR's impact on mortality.

Furthermore, we were unable to control for other interventions implemented contemporaneously in hospitals; hence, the effects might be overestimated while those activities take place in hospitals with EHR adoption. Yet, it has been over 10 years since IOM, CMS, AHRQ, and the Joint Commission on Accreditation of Healthcare Organizations introduced multiple interventions for healthcare quality improvement. We believe that similar activities should be nationally implemented, and the effect of EHR or computerized physician order entry adoption could overwhelm the effect of this selection-history bias.

In addition, using the posttest-only control study design, we assumed the preliminary risk-adjusted mortality rates were the same between hospitals with and without an EHR, or hospitals with and without a subsystem. However, the disparity of mortality rates between the two groups may be bigger in large states, where the sample hospitals are located. Given this scenario, our results may understate the influence of an EHR adoption on the mortality.

Our results are also limited by the cross-sectional data, precluding the establishment of causality between EHR and mortality rates. However, using propensity score analysis, our results provide strong evidence for the relationship between computerized physician order entry adoption and reduction in mortality rates.

We also recognize that relying on patients' risk-adjusted mortality rates from CMS secondary administrative data may cause misclassification due to adjustment errors, coding errors, or lack of specificity. Owing to this constraint, we need to assume hospital respondents had the same understanding of different terms of EHR subsystems, and that non-responsive hospitals were equally distributed in the two comparison groups. Despite these limitations, the AHA database is nationally representative and has been used for academic research for more than a decade. The liability and data validity is reliable.

Last but not least, although AMI and CHF are two common causes of hospitalization, and their measures are generally regarded as valid indicators of hospital quality, again, the adoption of these subsystems might have different effects on measures of other clinical conditions or outpatient settings. Finally, we cannot entirely discount the possibility that any of our significant findings occurred by chance alone.

Policy Implications

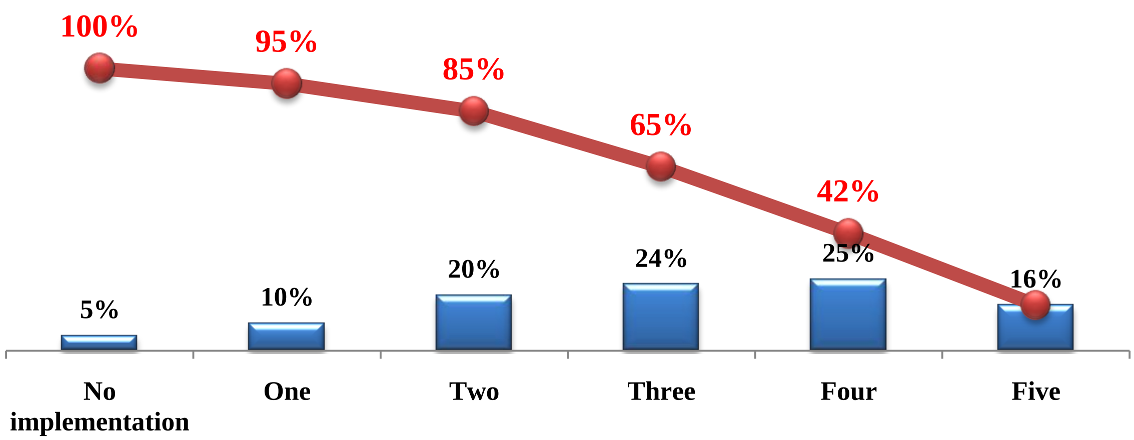
Overall, this study suggests that EHR adoption is a critical strategy for the benefit of patients. These positive findings support the recommendations made by the Institute of Medicine I.O.M [19], the US Department of Health and Human Services [16], the National Coordinator for Health Information Technology [92], and various existing literature [22, 26, 28, 29, 35] to adopt EHR systems widely. Policymakers should promote EHR initiatives and develop nationwide EHR infrastructures that facilitate their adoption.

Yet, given the limited health care resources, a computerized physician order entry should be the first priority. Our results support the definition of a qualified electronic health record in the HITECH Act, which requires a physician order entry system.

Nevertheless, it is notable that the presence of electronic clinical documentation, clinical decision support and physician order entry requirements in the Section 3000 (13) (B) would not be sufficient for meeting the goal of meaningful use. Given our results, governments should comply with all five subsystems for a qualified EHR. Strategy plans for nationwide EHR adoption and budget allocation on the adoption of distinct EHR components may need to be realigned. For better success, national coordinators should take into account the adoption magnitude, number of relevant EHR subsystems, and priority population in the alignment.

To date, although 95% of sample hospitals have demonstrated some level of adoptions of EHR systems, only 16% of sample hospitals have adopted five subsystems in at least one unit in 2008. [See Figure 3] Also, only 16% of sample hospitals fully adopted computerized physician order entry.

Figure 4. Distribution of Number of Subsystems among Sample Hospitals in 2008



Beyond these legislative requirements, a lack of integration of necessary components of EHR may increase operational difficulties for the clinical workforce, reduce efficacy of EHR systems (or even be harmful), and reduce the capability to capture and query information relevant to health care quality.

We suggest that systematic efforts to encourage nationwide adoption of computerized physician order entry should be a priority. Further, to maximize benefits of an EHR adoption, health care providers should continuously be trained for computerized physician order entry adoption and this training requirement should be included in the EHR certification criteria and final rule of meaningful use of the HITECH Act.

Clinical Implications

At the hospital level, managers may need to identify which EHR subsystems are most important and select the right subsystems by prioritizing specific population groups. We also need to inform decision-makers that a systematic adoption with all departments involved may lead to better efficacy. With the incentives provided by the government helping to facilitate the process, we believe that hospital managers should accelerate decisions to adopt EHRs. Given a good infrastructure, accelerating the computerized physician order entry adoption across all units in a hospital may also avoid information confusion due to partial implementation. From the patients' viewpoint, the computerized physician order entry adoption status of a hospital may be worthwhile information to consult when considering hospitalization options.

Future Research

To build on the findings of this study, future studies need to measure additional outcomes, such as readmission rates, patient satisfaction, and providers' turnout time, to address the effects more comprehensively. Using nationally representative datasets, including all hospitals, to address the impact of progressively nationwide EHR adoption can be also of interest. Further, it would be informative to test various combinations of EHR components so that decision-makers may choose the most effective combinations of EHR subsystems, given the existing adoption conditions. Also, cost-effective analyses should be of interest along with nationally adopted EHRs because high effective systems may be too costly for health care institutions to afford. Lastly, given the complex clinical nature and the intricacy of the health system, one may establish research on various measurements while replicating our results in different settings and with different populations.

CONCLUSION

This study fills a significant gap in the previous literature by not only documenting the significant number of subsystems required for better patient outcomes, but also by documenting the effects of distinct EHR subsystems simultaneously.

Our results indicate significantly better outcomes with an increase in the number of subsystems. It is worth noting that, however, that AMI is more amenable to the EHR adoption than CHF. Optimal results were achieved in AMI and CHF when hospitals fully adopted at least 3 and 5 subsystems, respectively. The results also demonstrate that despite the benefits of a holistic EHR adoption, computerized physician order entry is the most significant functionality. Yet, the prevalence of computerized physician order entry is still very low across all U.S hospitals. Our findings additionally indicate that hospitals with a subsystem adopted across all units had significantly lower mortality rates than those with a subsystem only in some units.

The HITECH Act set aside $19 billion to promote EHR use with the underlying assumption that more EHR is better. However, our results suggest that the final rule of EHR meaningful use needs to be aligned with the factors such as number of subsystems, the adoption status in a hospital, and specific EHR subsystems. Future research is needed to investigate the different impacts of various combinations of EHR subsystems as well as in different clinical settings and with different populations.

APPENDICES

Table 6. Characteristics of Sample U.S. Acute Care Hospitals by Functionality Adoption Status

	Electronic Health Record Subsystems									
	Computerized Physician Order Entry		**Decision Support System**		**Electronic Clinical Documentation**		**Barcode System**		**Lab/Radiology Test Results Viewing System**	
	Across all units	No implementation	Across all units	No implementation	Across all units	No implementation	Across all units	No implementation	Across all units	No implementation
Characteristic (%)	155 (16%)	610 (63%)	155 (16%)	417 (43%)	109 (11%)	360 (37%)	116 (12%)	397 (41%)	397 (41%)	126 (13%)
Size										
Small (6–99 beds)	8%	71%	10%	55%	9%	43%	7%	45%	27%	22%
Medium (100–399 beds)	13%	66%	14%	43%	10%	37%	14%	40%	43%	11%
Large (≥400 beds)	38%	43%	31%	29%	19%	30%	13%	40%	50%	9%
Profitability Type										
For-profit hospital	10%	69%	13%	44%	10%	36%	21%	39%	27%	21%
Private nonprofit hospital	17%	62%	17%	42%	10%	36%	12%	41%	43%	12%
Public hospital	16%	61%	16%	46%	17%	42%	10%	46%	38%	16%
Hospital System										
Yes	20%	61%	21%	40%	13%	35%	16%	39%	43%	12%
No	12%	65%	12%	47%	9%	40%	8%	44%	39%	14%
Teaching Status										
Yes	45%	37%	32%	27%	24%	27%	12%	42%	52%	8%
No	12%	67%	14%	46%	9%	39%	12%	41%	39%	14%

	Electronic Health Record Subsystems									
	Computerized Physician Order Entry		**Decision Support System**		**Electronic Clinical Documentation**		**Barcode System**		**Lab/Radiology Test Results Viewing System**	
	Across all units	No implementation	Across all units	No implementation	Across all units	No implementation	Across all units	No implementation	Across all units	No implementation
Location										
Urban	17%	62%	18%	41%	12%	36%	13%	40%	43%	11%
Rural	5%	75%	5%	63%	5%	51%	2%	52%	16%	32%
Heart Transplant Services										
Yes	49%	38%	28%	32%	19%	26%	15%	43%	43%	11%
No	14%	64%	16%	43%	11%	38%	12%	41%	41%	13%
Cardiac Cath Lab										
Yes	22%	56%	21%	36%	13%	33%	15%	38%	49%	9%
No	10%	70%	12%	50%	9%	41%	9%	44%	32%	18%
Nurse Staff Ratio										
RN/Beds<1	8%	74%	8%	53%	6%	36%	9%	47%	25%	21%
1<=RN/Beds<2	16%	61%	17%	41%	12%	39%	14%	40%	44%	11%
RN/Beds>=2	36%	50%	31%	34%	19%	30%	8%	40%	53%	9%

Table 12a. Characteristics of Sample Hospitals by Computerized Physician Order Entry Adoption Status in 2008

	Adoption Status			
Characteristic (%)	Full Adoption Across all units 155 (16%)	Full Adoption at least in one unit 203 (21%)	No implementation 610 (63%)	P-Value for difference
Size				**<0.0001**
Small (6–99 beds)	8%	21%	71%	
Medium (100–399 beds)	13%	21%	66%	
Large (≥400 beds)	38%	19%	43%	
State				**0.038**
CA	11%	26%	63%	
IL	17%	19%	64%	
IN	16%	24%	60%	
MA	23%	30%	48%	
MI	21%	10%	69%	
MN	37%	18%	45%	
MO	12%	20%	68%	
NY	19%	20%	61%	
OH	11%	20%	69%	
PA	18%	18%	64%	
TX	13%	20%	67%	
WA	14%	36%	50%	
Profitability Type				0.424
For-profit hospital	10%	21%	69%	
Private nonprofit hospital	17%	20%	62%	
Public hospital	16%	22%	61%	
Member of Hospital System				**0.004**
Yes	20%	19%	61%	
No	12%	23%	65%	
Teaching Status				**<0.0001**
Yes	45%	18%	37%	
No	12%	21%	67%	
Location				**0.001**
Urban	17%	21%	62%	
Rural	5%	20%	75%	
Heart Transplant Services				**<0.0001**
Yes	49%	13%	38%	
No	14%	22%	64%	
Cardiac Catheterization Lab				**<0.0001**
Yes	22%	22%	56%	
No	10%	20%	70%	
Nurse Staff Ratio				**<0.0001**
RN/Beds<1	8%	18%	74%	
1<=RN/Beds<2	16%	23%	61%	
RN/Beds>=2	36%	14%	50%	

Table 12b. Characteristics of Sample U.S. Acute Care Hospitals by Decision Support System Adoption Status in 2008

	Adoption Status			
	Full Adoption Across all units	Full Adoption at least in one unit	No implementation	P-Value for difference
Characteristic (%)	155 (16%)	397 (41%)	417 (43%)	
Size				**<0.0001**
Small (6–99 beds)	10%	35%	55%	
Medium (100–399 beds)	14%	43%	43%	
Large (≥400 beds)	31%	40%	29%	
State				0.124
CA	9%	46%	45%	
IL	20%	42%	39%	
IN	24%	38%	38%	
MA	28%	33%	40%	
MI	13%	36%	51%	
MN	21%	42%	37%	
MO	23%	37%	40%	
NY	7%	40%	52%	
OH	16%	40%	44%	
PA	15%	47%	38%	
TX	19%	36%	45%	
WA	18%	43%	39%	
Profitability Type				0.811
For-profit hospital	13%	43%	44%	
Private nonprofit hospital	17%	41%	42%	
Public hospital	16%	38%	46%	
Member of Hospital System				**0.001**
Yes	21%	40%	40%	
No	12%	41%	47%	
Teaching Status				**<0.0001**
Yes	32%	40%	27%	
No	14%	41%	46%	
Location				**<0.0001**
Urban	18%	41%	41%	
Rural	5%	33%	63%	
Heart Transplant Services				0.095
Yes	28%	40%	32%	
No	16%	41%	43%	
Cardiac Catheterization Lab				**<0.0001**
Yes	21%	43%	36%	
No	12%	38%	50%	
Nurse Staff Ratio				**<0.0001**
RN/Beds<1	8%	39%	53%	
1<=RN/Beds<2	17%	42%	41%	
RN/Beds>=2	31%	34%	34%	

Table 12c. Characteristics of Sample U.S. Acute Care Hospitals by Electronic Clinic Documentation Adoption Status in 2008

Characteristic (%)	Adoption Status Full Adoption Across all units 109 (11%)	Full Adoption at least in one unit 500 (52%)	No implementation 360 (37%)	P-Value for difference
Size				**0.001**
Small (6–99 beds)	9%	47%	43%	
Medium (100–399 beds)	10%	53%	37%	
Large (≥400 beds)	19%	52%	30%	
State				**0.004**
CA	8%	48%	44%	
IL	13%	54%	33%	
IN	15%	50%	34%	
MA	13%	50%	38%	
MI	3%	58%	39%	
MN	32%	42%	26%	
MO	20%	38%	42%	
NY	5%	52%	43%	
OH	9%	55%	36%	
PA	9%	60%	32%	
TX	13%	53%	34%	
WA	14%	39%	46%	
Profitability Type				**0.05**
For-profit hospital	10%	55%	36%	
Private nonprofit hospital	10%	53%	36%	
Public hospital	17%	42%	42%	
Member of Hospital System				0.129
Yes	13%	52%	35%	
No	9%	51%	40%	
Teaching Status				**<0.0001**
Yes	24%	49%	27%	
No	9%	52%	39%	
Location				**0.005**
Urban	12%	52%	36%	
Rural	5%	44%	51%	
Heart Transplant Services				0.096
Yes	19%	55%	26%	
No	11%	51%	38%	
Cardiac Catheterization Lab				**0.015**
Yes	13%	54%	33%	
No	9%	50%	41%	
Nurse Staff Ratio				**0.008**
RN/Beds<1	6%	58%	36%	
1<=RN/Beds<2	12%	50%	39%	
RN/Beds>=2	19%	51%	30%	

Table 12d. Characteristics of Sample U.S. Acute Care Hospitals by Barcode System Adoption Status in 2008

	Adoption Status			
Characteristic (%)	Full Adoption Across all units 116 (12%)	Full Adoption at least in one unit 446 (46%)	No implementation 397 (41%)	P-Value for difference
Size				**0.003**
Small (6–99 beds)	7%	48%	45%	
Medium (100–399 beds)	14%	46%	40%	
Large (≥400 beds)	13%	47%	40%	
State				**<0.0001**
CA	5%	52%	43%	
IL	8%	46%	46%	
IN	22%	50%	28%	
MA	18%	38%	45%	
MI	15%	36%	49%	
MN	11%	50%	39%	
MO	26%	35%	38%	
NY	5%	50%	46%	
OH	12%	44%	44%	
PA	6%	53%	41%	
TX	19%	46%	35%	
WA	14%	50%	36%	
Profitability Type				0.095
For-profit hospital	21%	39%	39%	
Private nonprofit hospital	12%	48%	41%	
Public hospital	10%	45%	46%	
Member of Hospital System				**<0.0001**
Yes	16%	45%	39%	
No	8%	48%	44%	
Teaching Status				0.991
Yes	12%	46%	42%	
No	12%	47%	41%	
Location				**0.001**
Urban	13%	47%	40%	
Rural	2%	45%	52%	
Heart Transplant Services				0.799
Yes	15%	43%	43%	
No	12%	47%	41%	
Cardiac Catheterization Lab				**0.007**
Yes	15%	46%	38%	
No	9%	47%	44%	
Nurse Staff Ratio				0.097
RN/Beds<1	9%	44%	47%	
1<=RN/Beds<2	14%	46%	40%	
RN/Beds>=2	8%	52%	40%	

Table 12e. Characteristics of Sample U.S. Acute Care Hospitals by Test Results Viewing System Adoption Status in 2008

Characteristic (%)	Adoption Status: Full Adoption Across all units 397 (41%)	Full Adoption at least in one unit 446 (46%)	No implementation 126 (13%)	P-Value for difference
Size				<0.0001
Small (6–99 beds)	27%	51%	22%	
Medium (100–399 beds)	43%	46%	11%	
Large (≥400 beds)	50%	41%	9%	
State				0.001
CA	39%	46%	15%	
IL	55%	35%	10%	
IN	59%	36%	5%	
MA	43%	50%	8%	
MI	36%	48%	16%	
MN	39%	50%	11%	
MO	34%	55%	11%	
NY	35%	52%	13%	
OH	42%	52%	7%	
PA	38%	42%	20%	
TX	35%	44%	21%	
WA	43%	57%	0%	
Profitability Type				0.02
For-profit hospital	27%	51%	21%	
Private nonprofit hospital	43%	46%	12%	
Public hospital	38%	46%	16%	
Member of Hospital System				0.500
Yes	43%	46%	12%	
No	39%	47%	14%	
Teaching Status				0.01
Yes	52%	40%	8%	
No	39%	47%	14%	
Location				<0.0001
Urban	43%	46%	11%	
Rural	16%	52%	32%	
Heart Transplant Services				0.855
Yes	43%	47%	11%	
No	41%	46%	13%	
Cardiac Catheterization Lab				<0.0001
Yes	49%	42%	9%	
No	32%	50%	18%	
Nurse Staff Ratio				<0.0001
RN/Beds<1	25%	54%	21%	
1<=RN/Beds<2	44%	45%	11%	
RN/Beds>=2	53%	38%	9%	

Table 13. Distribution of subsystems in the existence of each subsystem adoption in 2008 (% Hospitals)

	Subsystem Adoption				
Existence of	Computerized Physician Order Entry (CPOE)	Decision Support System (DS)	Electronic Clinical Documentation (ECD)	Barcode System (BC)	Lab Test Result Viewing System (LR)
ECD (N=609)	43%	66%	100%	65%	93%
LR (N=841)	41%	62%	67%	63%	100%
DS (N=552)	51%	100%	73%	70%	95%
CPOE (N=360)	100%	78%	73%	66%	96%
BC (N=568)	42%	68%	69%	100%	93%

Note: Given the left-column subsystem in place, percentage of hospitals with the top-row subsystem adoption is shown.
ECD-Electronic Clinic Documentation
LR-Lab Test Result Viewing System
DS-Decision Support System
CPOE-Computerized Physician Order Entry
BC-Barcode System

Table 14. Distribution and Impact of Electronic Health Record Subsystem Adoptions among Sample Hospitals on Hospital Cardiac Risk-Adjusted Mortality Rates

Number of Subsystems Adopted	Computerized Physician Order Entry	Decision Support	Electronic Clinic Documentation	Barcode System	Lab Test Result Viewing System	Frequency	%	Coefficients	
								AMI	CHF
0						52	5.37		
1	√					2	0.21	**-1.33*****	**-0.57****
1		√				6	0.62		
1			√			17	1.75		
1				√		11	1.14		
1					√	59	6.09		
2	√		√			2	0.21		
2		√	√			3	0.31		
2			√	√		13	1.34		
2	√				√	19	1.96		
2		√		√		8	0.83		
2			√		√	64	6.6		-1.50**
2				√	√	53	5.47		
2	√			√		2	0.21		
2	√	√				2	0.21		
2		√			√	25	2.58		
3	√	√	√			4	0.41		
3	√	√			√	20	2.06		
3	√		√	√		1	0.1		
3	√		√		√	18	1.86		
3	√			√	√	14	1.44		
3		√	√	√		4	0.41		
3		√	√		√	51	5.26		
3			√	√	√	69	7.12		
3		√		√	√	47	4.85		
4	√	√	√	√		1	0.1		
4	√	√	√		√	57	5.88		
4	√		√	√	√	21	2.17		
4		√	√	√	√	127	13.11		-3.11*
4	√	√		√	√	40	4.13		
5	√	√	√	√	√	157	16.2		

Note: Only significant results were shown. *p<0.1; **p<0.05; ***p<0.01

Table 15a. Correlations among Presence of Subsystems and Number of Subsystems

	CPOE	Decision Support	Electronic Clinic Documentation	Barcode System	Test Result Viewing System	Number of subsystems				
						1	2	3	4	5
CPOE	1.000					-0.2391*	-0.2467*	-0.1395*	0.1355*	0.5719*
Decision Support	0.3275*	1.000				-0.3373*	-0.3710*	-0.0191	0.4064*	0.3822*
Electronic Clinic Documentation	0.1536*	0.2462*	1.000			-0.3067*	-0.2042*	0.0187	0.2522*	0.3381*
Barcode System	0.1083*	0.2558*	0.1562*	1.000		-0.3149*	-0.1894*	0.0067	0.2157*	0.3695*
Test Result Viewing System	0.2116*	0.2765*	0.2236*	0.2168*	1.000	-0.2404*	-0.0365	0.1517*	0.2206*	0.1715*

Table 15b. Correlations between Subsystem Adoption Statuses

		Computerized Physician Order Entry		**Decision Support**		**Electronic Clinic Documentation**		**Barcode System**		**Test Result Viewing System**	
		All	**One**	**All**	**One**	**All**	**One**	**All**	**One**	**All**	**One**
Computerized Physician Order Entry	**All**	1.000									
	One	-0.2265*	1.000								
Decision Support	**All**	0.4154*	-0.0422	1.000							
	One	0.0223	0.1194*	-0.3660*	1.000						
Electronic Clinic Documentation	**All**	0.3733*	-0.0541	0.3979*	-0.015	1.000					
	One	-0.0421	0.0344	-0.0783*	0.1187*	-0.3676*	1.000				
Barcode System	**All**	0.1261*	0.0187	0.1588*	0.0909*	0.1770*	0.032	1.000			
	One	0.0203	0.0214	0.007	0.1116*	-0.037	0.0779*	-0.3467*	1.000		
Test Result Viewing System	**All**	0.1977*	0.0665*	0.2232*	0.1164*	0.3037*	0.032	0.1800*	0.030	1.000	
	One	-0.0946	0.0144	-0.1305*	0.007	-0.2115*	0.059	-0.0850*	0.056	-0.7660*	1.000

Note: All- Full adoption across all units in a hospital
One-Full adoption in at least one but not all units in a hospital
*Significant at the 0.05 level

Table 15c. Correlations among Dependent Variables and Primary Independent Variables

		RSMR_AMI[a]	RSMR_HF[b]	EHR	Number of Subsystem	Number of subsystems				
						1	**2**	**3**	**4**	**5**
RSMR_AMI[a]		1.0000								
RSMR_HF[b]		0.3615*	1.0000							
EHR		-0.1412*	-0.0944*	1.0000						
Number of Subsystem		-0.1862*	-0.1090*	0.7157*	1.0000					
Number of subsystems	1	0.1133*	0.0829*	-0.7796*	-0.4749*	1.0000				
	2	0.0675*	-0.0030	0.2095*	-0.3611*	-0.1634*	1.0000			
	3	-0.0170	0.0150	0.2346*	-0.0090	-0.1829*	-0.2748*	1.0000		
	4	-0.0550	-0.0030	0.2467*	0.4054*	-0.1923*	-0.2890*	-0.3236*	1.0000	
	5	-0.1254*	-0.1033*	0.1859*	0.6186*	-0.1450*	-0.2179*	-0.2439*	-0.2565*	1.0000
Computerized Physician Order Entry		-0.1608*	-0.0954*	0.3132*	0.6012*	-0.2391*	-0.2467*	-0.1395*	0.1355*	0.5719*
Decision Support		-0.1556*	-0.0920*	0.4517*	0.7061*	-0.3373*	-0.3710*	-0.019	0.4064*	0.3822*
Electronic Clinic Documentation		-0.0786*	-0.0670*	0.4488*	0.5922*	-0.3067*	-0.2042*	0.019	0.2522*	0.3381*
Barcode System		-0.061	-0.017	0.4390*	0.5839*	-0.3149*	-0.1894*	0.007	0.2157*	0.3695*
Test Result Viewing System		-0.1148*	-0.061	0.5827*	0.5642*	-0.2404*	-0.037	0.1517*	0.2206*	0.1715*

		RSMR_AMI[a]	RSMR_HF[b]	EHR	Number of Subsystem	Number of subsystems				
						1	2	3	4	5
CPOE	**All[c]**	-0.1792*	-0.1536*	0.1867*	0.4559*	-0.1455*	-0.2117*	-0.1460*	0.0635*	0.5034*
	One[d]	-0.028	0.026	0.2029*	0.3006*	-0.1521*	-0.1010*	-0.033	0.1034*	0.2225*
Decision Support	**All[c]**	-0.1398*	-0.0827*	0.1874*	0.3654*	-0.1461*	-0.1915*	-0.042	0.1001*	0.3194*
	One[d]	-0.051	-0.03	0.3142*	0.4364*	-0.2299*	-0.2296*	0.013	0.3343*	0.1445*
Electronic Clinic Documentation	**All[c]**	-0.0795*	-0.026	0.1506*	0.3357*	-0.1174*	-0.1518*	-0.0974*	0.063	0.3487*
	One[d]	-0.026	-0.048	0.3388*	0.3603*	-0.2224*	-0.1015*	0.0796*	0.2043*	0.1064*
Barcode System	**All[c]**	-0.031	-0.02	0.1575*	0.3059*	-0.1228*	-0.1448*	-0.058	0.0873*	0.2730*
	One[d]	-0.04	-0.004	0.3303*	0.3761*	-0.2304*	-0.0921*	0.045	0.1557*	0.1858*
Test Result Viewing System	**All[c]**	-0.1052*	-0.051	0.2681*	0.3808*	-0.1740*	-0.1355*	0.011	0.1061*	0.2689*
	One[d]	0.026	0.009	0.1316*	0.008	0.008	0.1087*	0.0919*	0.045	-0.1485*

Note: *Significant at the 0.05 level

a. RSMR_AMI –Risk-adjusted mortality rates of patients with acute myocardial infarction;
b. RSMR_HF- Risk-adjusted mortality rates of patients with heart failure;
c. All- Full adoption across all units in a hospital;
d. One-Full adoption in at least one but not all units in a hospital

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Notes

[i] As stated earlier, computerized physician order entry, electronic clinical documentation, and decision support are required components of a qualified EHR in the HITECH Act.

[ii] Clinical notes consist of medication administration, daily charting, physical assessments and admission notes. **12.** Marr PB, Duthie E, Glassman KS, et al. Bedside terminals and quality of nursing documentation. *Comput Nurs.* Jul-Aug 1993;11(4):176-182. Daily charting includes patients' daily functional activities such as vital signs, food, elimination, mobility and patient teaching. Physical assessment summaries comprise all kinds of status assessments (e.g. skin status or respiratory status). Admission notes contain information on allergies, health behaviors (e.g. physical activity or smoking or sleep patterns), physical assessments (e.g. temperature and neurological status), discharge planning and initial care plans.[7]

[iii] Modern diversified radiology departments typically use Picture Archiving and Communication Systems (PACS) for most of their imaging. A PACS system is an imaging system (usually with accessible reports), and these images can generally be made available outside the radiology and nuclear medicine departments, in hospitals, clinics, offices, and physician's homes.**4.** Henkin RE, Harolds JA. Health information technology and the electronic medical record. *Clin Nucl Med.* Oct 2010;35(10):788-789.