

# Association of EMR Adoption with Minority Health Care Outcome Disparities in US Hospitals

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**Objectives:** Disparities in healthcare among minority groups can result in disparate treatments for similar severities of symptoms, unequal access to medical care, and a wide deviation in health outcomes. Such racial disparities may be reduced via use of an Electronic Medical Record (EMR) system. However, there has been little research investigating the impact of EMR systems on the disparities in health outcomes among minority groups. **Methods:** This study examined the impact of EMR systems on the following four outcomes of black patients: length of stay, inpatient mortality rate, 30-day mortality rate, and 30-day readmission rate, using patient and hospital data from the Medicare Provider Analysis and Review and the Healthcare Information and Management Systems Society between 2000 and 2007. The difference-in-difference research method was employed with a generalized linear model to examine the association of EMR adoption on health outcomes for minority patients while controlling for patient and hospital characteristics. **Results:** We examined the association between EMR adoption and the outcomes of minority patients, specifically black patients. However, after controlling for patient and hospital characteristics we could not find any significant changes in the four health outcomes of minority patients before and after EMR implementation. **Conclusions:** EMR systems have been reported to support better coordinated care, thus encouraging appropriate treatment for minority patients by removing potential sources of bias from providers. Also, EMR systems may improve the quality of care provided to patients via increased responsiveness to care processes that are required to be more time-sensitive and through improved communication. However, we did not find any significant benefit for minority groups after EMR adoption.

**Keywords:** Electronic Medical Records, Length of Stay, Mortality

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## I. Introduction

The practice of medical care in the United States varies in relation to patient race and ethnicity [1]. There are multiple roots of these healthcare disparities, ranging from differences in physician and patient perceptions and communication during clinical encounters, to differences in the ways that different racial and ethnic groups relate to the institutions and systems that finance and provide care [2]. How information is presented, managed, and exchanged contributes to healthcare disparities. Therefore, the use of Electronic Medical Records (EMRs) could potentially reduce disparities.

The purpose of EMR systems is to retain, organize, and communicate medical information in a uniform manner. EMRs have the potential to make healthcare providers' decisions more consistent and objective, while ensuring that best practices are pursued [3]. EMRs provide evidence-based decision support to the healthcare provider at the point of service and can lead to timely and informed medical decision making. Such standardization has the potential to provide benefits to members of racial and ethnic minority populations that have disproportionately experienced sub-standard care.

While a growing number of studies have examined the use of EMRs to improve the efficiency of medical care delivery, surprisingly few studies have explored the impact of EMRs on reducing health disparities between racial and ethnic groups. Thus, the aim of this study was to investigate the differential impact of EMR adoption on the outcomes of care among members of minority groups. Our hypothesis was that the adoption of an EMR system by a hospital or hospital system would provide benefits to members of disadvantaged minority groups who had historically experienced lower-quality medical outcomes compared to non-Hispanic white patients.

The hospital EMR adoption rate increased from 9.4% in 2008 to 59.4% in 2013 [4]. The Healthcare Information and Management Systems Society (HIMSS) has tracked changes during the implementation of EMR systems. Using their collected information, we investigated whether the adoption of EMR systems reduced racial and ethnic disparities in health outcome measurements by comparing EMR-adopting hospitals to hospitals that have yet to implement an EMR system.

These care quality measures were calculated using linked Medicare claims data for patients receiving care in each hospital for two years before and after the adoption of an EMR system, compared to patient data from hospitals that had not adopted an EMR over the same time period. Thus, our main methodological approach was to use a difference-in-difference design to examine changes in outcome disparities. Analyses were adjusted for the characteristics of patients and hospitals using data from the Medicare Beneficiary Summary File and the HIMSS data.

Poor access to care among African Americans and Hispanics is reflected in substantially lower rates of employment-based insurance coverage, lack of a regular source of medical care, and ethnic/cultural mismatches with care providers. These factors may also reduce the continuity of care among these disadvantaged populations relative to non-Hispanic whites and may diminish the engagement and trust be-

tween patient and provider, reducing the quality of medical decision-making. The Institute of Medicine found racial disparities across a wide range of disease areas, clinical services, and clinical settings, even after clinical factors, including age, disease progression, comorbid conditions, and severity of illness, were taken into account [2]. They concluded that prejudices, biases, and negative racial stereotypes may be a potential source of the disparity and proposed "evidence based guidelines" among the solutions. In addition, there are abundant research findings that racial and ethnic disparities in health care can be explained in part by minorities' disproportionate receipt of care from certain institutions where all patients, irrespective of race, tend to experience worse outcomes [5]. There is some concern that regulatory policies aimed to reduce poor outcomes may disproportionately impact minority-serving institutions, perhaps increasing racial disparities [6].

Previous studies have demonstrated disparities in both the outcomes and process of care. Compared with white patients with diabetes, African Americans with diabetes were less likely to have received the recommended processes of care metrics, including glycated hemoglobin (HbA1c) and lipid measurements [7,8]. Another study [9] found that compared with white patients, black and Hispanic patients experienced substantially longer wait times from the start of dialysis to being added to the kidney transplant waiting list.

Furthermore, previous health services research suggests that there are racial disparities in health outcomes. Some studies have found that black patients experienced a higher 30-day readmission rate (24.8%) compared to white patients (22.6%) according to Medicare beneficiary data [5,10]. Other studies found that black patients admitted with pneumonia had a longer length of stay than white patients (incidence rate ratio: 1.19). Moreover, black patients had a higher inpatient mortality rate than white patients after cardiovascular procedures and cancer resections; the odds ratios of inpatient mortality for black patients relative to white patients are 1.21 (carotid endarterectomy), 1.21 (aortic valve replacement), 1.16 (coronary artery bypass graft), 1.32 (abdominal aortic aneurysm repair), 1.08 (resection for lung cancer), 1.32 (cystectomy of the bladder), 1.57 (esophagectomy), and 1.27 (pancreatic resection).

Despite the projection that the minority population is expected to rise to 56% of the total US population, prior research on racial and ethnic disparities in healthcare has failed to identify methods of reducing these disparities [11]. This study was an expansion of the work by Lee et al. [12], which investigated the relationship between EMR adoption

and health outcomes of the general population; however, they did not focus on the outcome disparities among minorities. Our study investigated the association between EMR adoption and the health outcomes of minorities, including length of stay, inpatient mortality rate, 30-day mortality rate, and 30-day readmission rate. This study was approved by the Institutional Review Board (IRB) at the University of Texas Medical Branch (IRB No. 09-054).

## II. Methods

### 1. Data Sources

In this study, we employed four primary data sources: 1) HIMSS data, 2) Provider of Service (POS) files, 3) Medicare enrollment files and 4) the 5% Medicare Provider Analysis and Review (MEDPAR) data from 2000 to 2007. The HIMSS data was sampled from the American Hospital Association (AHA) annual survey of hospitals, which provides information on health IT applications for more than 3,000 US hospitals. Medicare enrollment files provide patient socio-demographic characteristics, such as sex, age, insurance and race. The POS file provides information on providers, including characteristics of institutional providers. The MEDPAR file contains claims data on Medicare beneficiaries hospitalized in Medicare-certified inpatient hospitals and skilled nursing facilities (SNF).

### 2. Establishment of the Study Cohort

This study identified more than 2,600 unique acute-care hospitals with more than 100 beds between 2000 and 2007. We excluded hospitals if they were not consecutively observed over the entire 8-year study period, if they did not have a Medicare provider number, or if they adopted any components of a basic EMR before 2002. After excluding hospitals that did not meet the eligibility criteria, 708 acute-care hospitals were finally included in our analyses.

Using HIMSS data, we identified the year of adoption of a basic EMR, defined as a computerized patient record that is supported by a clinical data repository and has clinical decision-support capabilities [13,14]. The four outcomes were length of stay, inpatient mortality rate, 30-day mortality rate, and 30-day readmission rate. The sample included patients who were older than 65 years, had not been enrolled in HMOs, and had both Medicare Parts A and B for the entire 12 months before admission.

### 1) Outcome variables

#### (1) Length of stay

This sample only included stays shorter than 365 days in which the patient was discharged alive. To correct for data skewness, we excluded admissions in which the length of stay was more than 3 standard deviations from the mean. The final sample size for the length of stay was 360,105.

#### (2) Inpatient mortality and 30-day mortality rate

This sample included hospital stays no longer than 365 days for all patients, including patients who died in the hospital or were discharged alive. The inpatient mortality rate was calculated by the number of patients who died during hospital stays over the total number of admitted patients. The 30-day mortality rate was defined as the number of patients who died within 30 days of admission over the total number of patients admitted. The final sample size for mortality was 403,566.

#### (3) 30-day readmission rate

The accumulation of claims from a beneficiary's date of admission to an inpatient hospital to the date of discharge represents one stay in the MEDPAR file. We only retained data for hospitalizations lasting less than 365 days in which the patient was discharged alive. The 30-day readmission rate was defined as the number of patients discharged and readmitted to any acute hospital within 30 days of discharge over the total number of patients discharged alive. For the multiple readmission rate, one admission per year was randomly selected. The final sample size for 30-day readmission was 237,081.

### 2) Independent variables

Medicare enrollment files were utilized to obtain patients' demographic information, including age, sex, and race. Information on discharge diagnosis related group (DRG) was obtained from the Center for Medicare & Medicaid Services and MEDPAR files. To construct a variable indicating comorbid conditions measured by the Elixhauser index, we utilized inpatient and physician claims from MEDPAR, Outpatient Statistical Analysis files, and carrier files measured for the 12 months prior to initial hospitalization [15]. Structural characteristics of hospitals were obtained from the POS files. We measured teaching status as a binary variable defined as either none or any. We measured hospital size based on bed size and categorized hospitals into quartiles. Ownership status of hospitals was categorized as not-for-

profit, profit, or government.

### 3. Statistical Analysis

To examine the association of EMR adoption on health outcomes for minority patients, we used a difference-in-difference research design based on observational research comparing outcomes two years before EMR adoption and two years after EMR adoption. The difference-in-difference is a statistical technique used to estimate treatment effects by comparing before and after treatment differences in outcome between a control and a treatment group [16]. In our study, the treatment group was composed of hospitals adopting EMR systems between 2002 and 2005, and the control group contained hospitals who did not adopt an EMR system during the same period.

During the study period, 425 hospitals adopted an EMR (Table 1): 159 hospitals in 2002, 77 in 2003, 46 in 2004, and 143 in 2005. Hospitals not adopting EMR systems were randomly assigned to match the distribution for the year of adoption for hospitals adopting EMR systems (Table 2): 106 in 2002, 51 in 2003, 30 in 2004, and 96 in 2005. In other words, because 159 hospitals that had adopted EMR systems accounted for 37% of the total 425 hospitals that had adopted EMR systems in 2002, we randomly matched 106 out of the 283 total (37%) non-EMR-adoption hospitals for this particular year in the non-EMR-adoption group.

We considered two groups of hospitals: hospitals adopting EMR systems (treatment group) and hospitals not adopting EMR systems (control group). In the treatment group, we selected hospitals that had adopted EMR systems in their third year to compare two years before and two years after EMR system adoption. Then, we multiplied 1) EMR group, 2) year of EMR adoption, and 3) black patients to determine whether EMR adoption could improve outcomes for black patients. Our regression model is expressed as

$$Y_{it} = \alpha + \beta_1 EMR_{it} + \beta_2 after\_EMR_{it} + \beta_3 Black_i + \beta_4 EMR_{it} * after\_EMR_{it} + \beta_5 EMR_{it} * after\_EMR_{it} * Black + \beta_6 Pat\_Charac + \beta_7 Hosp\_Charac + Time + \epsilon_{it}$$

Table 1. EMR-adoption group (treatment group)

Before adoption	Adoption (number of hospital)	After adoption
2000–2001	2002 (159)	2003–2004
2001–2002	2003 (77)	2004–2005
2002–2003	2004 (46)	2005–2006
2003–2004	2005 (143)	2006–2007

EMR: Electronic Medical Record.

where *i* represents hospitals, *t* represents time of year, *Y* represents outcome; *EMR* represents EMR-adoption hospitals coded as 1 if EMR was adopted and 0 if not; *After\_EMR* represents years after EMR adoption; *Black* represents patients of African-American descent; *Pat\_Charac* represents patient characteristics, including sex, age, and race (either white or black), and comorbidity; and *Hosp\_Charac* represents hospital characteristics, including teaching status, bed size, and ownership.

The key independent variables are interaction terms of *EMR*, *after\_EMR*, and *Black*. If  $\beta_4$  or the coefficient of *EMR* and *after\_EMR* (or odds) was significantly negative (or less than 1), we could confirm that EMR adoption was negatively associated with patient outcomes. Alternatively, if  $\beta_5$  or the coefficient of *EMR*, *after EMR*, and *Black* (or odds) was significantly negative (or less than 1), we could confirm that EMR adoption could improve patient outcomes for black patients. We used generalized linear models (GLMs) to investigate the link between EMR adoption and reduction in disparities in four health outcomes for black patients (i.e., length of stay, inpatient mortality rate, 30-day mortality rate, and 30-day readmission rate) after taking clinical (i.e., comorbidities) and demographic (i.e., age, sex, and race) characteristics of patients, structural (i.e., ownership type, teaching status, and bed size) characteristics of hospitals, and time (year) into account.

We used a GLM with binomial distribution and logit link for the models for (1) inpatient mortality rate, (2) 30-day mortality rate, and (3) 30-day readmission, and a GLM with normal distribution and log link for (4) length of stay. All statistical analyses were performed using STATA 14 (Stata-Corp, College Station, TX, USA).

### III. Results

The study cohort included patients admitted to 425 hospitals adopting EMR systems and 283 hospitals not adopting EMR systems over the study period as indicated in Tables 1 and 2. Table 3 presents patient, disease, and hospital characteristics.

Table 2. Non-EMR-adoption group (control group)

Before adoption	Adoption (number of hospital)	After adoption
2000–2001	2002 (106)	2003–2004
2001–2002	2003 (51)	2004–2005
2002–2003	2004 (30)	2005–2006
2003–2004	2005 (96)	2006–2007

EMR: Electronic Medical Record.

A larger proportion of patients were female (59%), aged between 76–85 (43%), and white (90.7%).

White patients accounted for 90.7% of the sample. The mean of the comorbidity index was 2.9. Slightly less than half of the hospitals were teaching hospitals, while not-for-profit hospital ownership accounted for the majority (78.1%). The number of beds in each type of hospital was equally distributed. Table 3 also shows descriptive statistics for the four outcomes: the mean length of stay was 5.62 days, inpatient mortality 4.4%, 30-day mortality 13.5%, and 30-day readmission 16.3%.

**Table 3. Descriptive statistics for patients and hospitals**

Variable	%	Average	SD
Patient characteristics (403,566 observations)			
Sex			
Male	41		
Female	59		
Age (yr)			
65–75	37		
76–85	43		
≥86	20		
Comorbidity		3	2
Race			
White	91		
Black	9		
Hospital characteristics (708 acute-care hospitals)			
Teaching			
Teaching hospital	43		
Non-teaching hospital	57		
Ownership			
Profit	7		
Not-for-profit	78		
Government	15		
Number of beds			
≤170	26		
171–260	26		
261–392	25		
≥393	23		
Outcomes (no. of observations)			
Length of stay (360,105)		6	6
Inpatient mortality (403,566)	4		20%
30-day mortality (403,566)	14		34%
30-day readmission (237,081)	16		37%

Table 4 presents the difference-in-difference GLM regression results of length of stay and inpatient mortality rate. In the first column (length of stay), the variables positively associated with length of stay are black race, older age groups (65–75 and 86 and over), higher comorbidity, and greater number of beds. As seen in the second column (inpatient mortality rate), we found that patients who were black males, had a higher comorbidity rate, and belonged to an older age group (76–85 and 86 and over) had an increased likelihood of experiencing inpatient mortality. In addition, government hospital ownership and number of beds from 261–362 were other factors linked to higher mortality rates.

Table 5 presents GLM regression results of 30-day readmission and 30-day mortality after discharge. As seen in the first column (30-day readmission rate), we found that patients who were black, males, had a higher comorbidity rate, and belonged to an older age group (76–85 and 86 and over) were more likely to have a higher 30-day readmission rate. Also, hospitals of not-for-profit ownership were more likely to have a higher 30-day readmission rate. As seen in the second column (30-day mortality rate), patient characteristics associated with higher 30-day mortality rates were male, older age, and higher comorbidity. The hospital characteristic associated with higher 30-day mortality rates was not-for-profit ownership.

However, we could not find any significant effect of EMR adoption, the years after EMR adoption, the interaction terms of the EMR adopted group, after years of EMR adoption and race in all four outcome regressions.

## IV. Discussion

EMR systems have been reported to support better coordinated care [3,12,17,18], thus encouraging appropriate treatment for minority patients by removing potential sources of bias from the providers [19]. Health IT systems could improve clinical care by detecting important clinical and socio-demographic risk factors for various conditions particularly relevant to minority patients. EMR systems may improve the quality of care provided to patients via increased responsiveness to care processes that are required to be more time-sensitive and through improved communication [20].

While a growing number of studies have examined the association between EMRs and health outcomes, surprisingly few studies have explored the impact of EMRs on outcome disparities among minorities. Thus, to fill this gap in the current literature, this study investigated the impact of EMR system adoption on disparities in health outcomes of



**Table 4. Association between EMR and outcomes using generalized linear model regression: length of stay (360,105) and inpatient mortality (403,566)**

	Length of stay		Inpatient mortality rate	
	Coefficient (SE)	95% CI	Odds ratio (SE)	95% CI
Sex				
Female (reference)				
Male	0.003 (0.004)	-0.005 to 0.011	1.304*** (0.018)	1.268 to 1.341
Age (yr)				
65-75 (reference)				
76-85	0.051*** (0.004)	0.042 to 0.060	1.403*** (0.024)	1.358 to 1.451
≥86	0.063*** (0.006)	0.051 to 0.076	2.266*** (0.042)	2.185 to 2.349
Comorbidity	0.070*** (0.001)	0.067 to 0.073	0.971*** (0.005)	0.961 to 0.982
Race				
White (reference)				
Black	0.098*** (0.013)	0.073 to 0.122	1.203*** (0.035)	1.136 to 1.274
EMR-adoption group	-0.021 (0.014)	-0.048 to 0.006	0.971 (0.025)	0.923 to 1.022
Years after of EMR adoption	0.006 (0.013)	-0.019 to 0.031	0.990 (0.030)	0.932 to 1.051
EMR-adoption group × years after of EMR adoption	0.004 (0.009)	-0.015 to 0.022	1.041 (0.032)	0.981 to 1.106
EMR-adoption group × years after of EMR adoption × black	0.000 (0.016)	-0.032 to 0.032	0.925 (0.049)	0.834 to 1.027
Ownership				
Profit (reference)				
Not-for-profit	0.018 (0.028)	-0.038 to 0.073	1.013 (0.062)	0.899 to 1.142
Government	0.023 (0.019)	-0.014 to 0.060	1.091*** (0.032)	1.030 to 1.156
Teaching	0.021* (0.013)	-0.004 to 0.046	1.026 (0.027)	0.974 to 1.081
Number of beds				
≤170 (reference)				
171-260	0.042*** (0.015)	0.012 to 0.072	1.028 (0.035)	0.962 to 1.098
261-392	0.083*** (0.015)	0.053 to 0.113	1.062*** (0.037)	0.991 to 1.138
≥393	0.121*** (0.017)	0.087 to 0.155	1.055 (0.042)	0.976 to 1.140
Constant	1.407*** (0.017)	1.373 to 1.441	-	-

EMR: Electronic Medical Record, SE: standard error, CI: confidence interval.

\* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.001$ .

black patients. However, we did not observe any significant changes in health outcomes before and after EMR system implementation. Moreover, we did not find evidence that EMR system implementation was associated with outcomes of black patients.

A possible reason for the lack of any significant association between EMR and healthcare outcomes of black patients could be the short-term effect of EMR adoption. We compared the outcomes two years before and after EMR adoption. Thus, no meaningful changes in health outcomes

of black patients were observed after EMR implementation, which might reflect a short-term effect of EMR implementation on patient outcomes. It has been reported that it may take several years for hospitals adopting EMR systems to fully capitalize on the clinical benefits after EMR implementation [18]. In particular, benefits from EMR on health outcomes may take longer than for process of care for minority populations. For example, Lee [21] found that greater health IT investment leads to shorter waiting times, and the waiting time reduction was greater for non-white than for white pa-

Table 5. Association between EMR and outcomes using generalized linear model regression: 30-day mortality (403,566) and 30-day readmission (237,081)

	30-day mortality rate		30-day readmission rate	
	Coefficient (SE)	95% CI	Odds ratio (SE)	95% CI
Sex				
Female (reference)				
Male	1.349*** (0.018)	1.314 to 1.384	1.139*** (0.011)	1.118 to 1.161
Age (yr)				
65–75 (reference)				
76–85	1.374*** (0.022)	1.332 to 1.417	1.032*** (0.012)	1.008 to 1.056
≥86	2.493*** (0.042)	2.412 to 2.576	1.046*** (0.015)	1.016 to 1.077
Comorbidity	1.202*** (0.004)	1.194 to 1.210	1.325*** (0.004)	1.317 to 1.334
Race				
White (reference)				
Black	1.113*** (0.031)	1.054 to 1.176	1.163*** (0.026)	1.113 to 1.216
EMR-adoption group	0.098 (0.021)	0.939 to 1.023	0.981 (0.020)	0.943 to 1.021
Years after of EMR adoption	1.024 (0.025)	0.976 to 1.074	1.002 (0.022)	0.959 to 1.046
EMR-adoption group × years after of EMR adoption	1.005 (0.030)	0.948 to 1.065	1.018 (0.022)	0.976 to 1.062
EMR-adoption group × years after of EMR adoption × black	0.937 (0.046)	0.852 to 1.031	0.953 (0.034)	0.888 to 1.023
Ownership				
Profit (reference)				
Not-for-profit	0.997 (0.039)	0.924 to 1.077	1.073*** (0.033)	1.011 to 1.139
Government	1.063** (0.026)	1.014 to 1.115	1.012 (0.023)	0.968 to 1.059
Teaching	1.007 (0.020)	0.969 to 1.048	1.003 (0.018)	0.967 to 1.039
Number of beds				
≤170 (reference)				
171–260	0.954* (0.026)	0.904 to 1.007	0.989 (0.024)	0.943 to 1.037
261–392	0.977 (0.027)	0.925 to 1.032	1.022 (0.024)	0.977 to 1.070
≥393	0.905*** (0.027)	0.853 to 0.960	0.996 (0.026)	0.945 to 1.049

EMR: Electronic Medical Record, SE: standard error, CI: confidence interval.

\* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.001$ .

tients. He concluded that minority populations could benefit from health IT in terms of process of care [21].

Also, eliminating healthcare disparities among minority groups may remain limited, even though the evidence of healthcare disparity among minority groups is substantial [22]. Acevedo-Garcia et al. [22] argued that an effort to eliminate disparities among specific groups is currently underway but will take more time. For example, this effort has focused on training providers to offer appropriate services through the use of EMR systems and to improve coordination of care [22].

There were some limitations in this study. First, for this

work, EMR was defined as computerized patient record systems (CPRS) supported by clinical decision-support (CDS) capabilities and a clinical data repository (CDR) [13,14]. Thus, the definition of EMR adoption was less restraining than those used in previous studies [23–25]. For example, Miller and Tucker [23] employed HIMSS data, but defined EMR adoption as four complete components of adoption including CDR, computerized physician order entry (CPOE), CDSS, and digitized physician documentation. Also, prior studies have used a more limited definition of EMR [24,25] that included IT systems, such as electronic medication administration records (eMAR) and nursing documentation.

This study used a more expansive definition of EMR systems because HIMSS data was incompatible with health IT systems, such as physician documents.

Second, we did not have access to in-depth data indicating the level of care regarding provider proficiency and reluctance related to the use of EMR systems in hospitals. Hence, if care providers are resistant to using an EMR system or are not IT-savvy for various reasons after EMR adoption, our data may be underestimated.

Lastly, there may have been unobserved confounding factors that might have impacted our findings. For example, organizational and management behavior may be correlated with health IT adoption. Although we controlled for structural characteristics of the hospital and patient clinical and demographic characteristics, EMR adoption behavior may vary in ways we could not observe in the data set, leading to bias in our results.

## Conflict of Interest

No potential conflict of interest relevant to this article was reported.

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