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The impact of electronic medical record systems on hospital efficiency

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Abstract: This study investigated whether hospitals across US that implemented electronic medical record systems (EMR) were more efficient than hospitals that did not implement EMR and examined control variable effects on hospital efficiency. This paper used the 2015 American Hospital Association datasets. To measure hospital efficiency, this research developed data envelopment analysis (DEA) models with four inputs (hospital beds, operating expenses, full-time physicians, and full-time registered nurses) and four outputs (operating revenue, operating margin, outpatient visits, and inpatient visits). To explore the control effect, this article used four control variables (location type, teaching hospital status, ownership status and region). The evidence showed that hospitals with larger bed counts, hospitals in metropolitan areas, teaching hospitals, non-governmental institutions, for-profit organisations, and hospitals in the Northeast with partial or full EMR systems were more efficient than the other groups.

Keywords: electronic medical records; hospital efficiency; size; location; teaching status; ownership status; region.

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1 Introduction

Electronic medical records (EMR) are the digital equivalent of medical records on paper. By implementing EMR, multiple healthcare providers can track patient data over an extended period of time. It can help identify those who are due for preventive checkups and screenings and can monitor whether patients meet certain health goals like vaccinations and blood pressure readings (USF Health, 2019).

Many expect that implementing EMR brings greater efficiency to hospitals because it can result in quicker access to patient information. Chaudhry et al. (2006) reported that health information technology improved the efficiency of medical care. Joos et al. (2006) specified that the majority of clinicians agreed that EMR systems helped with efficiency. Alternatively, Poissant et al. (2005) concluded that the impact on time spent documenting per patient using EMR devices was unfavourable, with increases of time ranging from 7.7% to 128.4%. DesRoches et al. (2010) showed that simply implementing an EMR would not improve processes in a hospital automatically. Rather, it is also necessary to implement policies that change how employees work and to give them reasons to use the system. However, most of the research supporting the benefits of EMR analyzed only single hospitals or used qualitative methods, thus limiting the ability to generalise findings (Kazley and Ozcan, 2008). To our best knowledge, no study has used all the following variables to determine hospital efficiency:

1 if the hospital has implemented an EMR system

2 the size of hospital

3 location of the hospital

4 if it is a teaching hospital or not

5 if the hospital is a non-profit or profit organisation

6 the region in which a hospital is located.

The main objective of this study is to gain insight on whether hospitals that have implemented EMR systems across US are more efficient than hospitals that have not implemented EMR systems, as well as identifying if any other factors could lead to a hospital's efficiency. Although various approaches measure efficiency in literature, data envelopment analysis (DEA) is one of the frequently used approaches that measure the performance of similar units under a multi-output and multi-input environment (Otay et al., 2017).

We will develop research hypotheses in the next section. The model development section will describe the methodology including the variables and analytical model. The results section focuses on the statistical results regarding electronic medical records in hospitals and presents their managerial implications. The conclusion section concludes and summarises our study.

2 Hypothesis development

This section discusses how we develop research hypotheses.

2.1 Effect of EMR on efficiency

Cherry et al. (2011) recommended best practices for adoption and implementation policies and for creating proper organisational practices related to EMRs. Bardhan and Thouin (2013) researched if the implementation of an EMR system associates with greater performance in terms of quality and whether hospitals with EMR systems are more likely to have overall lower operating expenses. Hillestad et al. (2005) found that effective EMR implementation could eventually save more than $81 billion a year by improving healthcare efficiency. Our study hypothesises that EMR systems have a positive impact in efficiency in hospitals.

Hypothesis 1 (H1): Hospitals with EMR systems are more efficient than hospitals without EMR systems.

2.2 Effect of hospital size and EMR on efficiency

Our study theorises that hospital size can impact an EMR system's success significantly. Kazley and Ozcan (2008) saw distinguishable results between hospitals grouped as small, medium, and large. This criterion is based on the number of beds and staff at each hospital. The rationale was that different sized hospitals would have different resources that impact how they operate. They showed that smaller hospitals have better efficiency ratings than their larger peers. Lee et al. (2015) found that hospitals with hospitalist care – medical specialty dedicated to the delivery of comprehensive medical care to hospitalised patients – had more efficiency with adoption of the digitised version of a patient's chart. Adler-Milstein et al. (2015) used hospital size and number of beds as variables in their study on hospital efficiency. Cho et al. (2018) was able to demonstrate hospital efficiency based on the number of beds and full-time employees (FTEs) including physicians and registered nurses. Poon et al (2004) saw a correlation between literacy levels in hospitals and the success of EMR implementation. It is possible that hospital size correlates with the literacy rates of hospital staff. Jha et al. (2009) conducted a study that showed larger hospitals were more likely to have EMR systems. Also, Bardhan and Thouin (2013) used number of beds as a variable. House et al. (2011) and Hillestad et al. (2005) used hospital size as a selection in their surveys. In our study, we want to investigate further into whether hospital size and EMR implementation status can impact hospital efficiency significantly.

Hypothesis 2 (H2): Hospital size and EMR implementation status may make an impact on hospital efficiency.

2.3 Effect of hospital location and EMR on efficiency

Being in a metropolitan or urban environment has many technical advantages for a hospital over being in a rural environment. One significant difference is the prevalence of high-speed broadband internet. Because of infrastructure, rural organisations may not have access to high-speed internet. Jha et al. (2009) found that metropolitan hospitals were more likely to have EMRs implemented. Eberth and Thomas (2017) found that hospitals in rural areas were less likely to have the infrastructure required to implement EMR systems properly. In their study, Houser et al. (2011) found the possibility of a perception among rural hospitals, specifically those in Alabama, that EMR implementation might not reduce costs. DesRoches et al. (2010) analyzed whether hospital location impacted adoption rates. They found that rural hospitals were less likely to have a system, while urban hospitals were more likely to have one. In their study, Adler-Milstein et al. (2015) used location, rural vs urban, as a variable on hospital efficiency. Cho et al. (2008) found numerous sources indicating differences in hospital resources between urban and rural settings. Furukawa (2011) found hospitals with EMR were more likely to be located in metro areas with higher median household income and educational attainment.. We hypothesise that hospitals with EMRs in metropolitan areas will be more efficient than those in rural areas.

Hypothesis 3 (H3): Hospital location and EMR implementation status may make an impact on hospital efficiency.

2.4 Effect of teaching hospital status and EMR on efficiency

Teaching hospital status is another possible variable in our study. In US, hospitals can be split between teaching hospitals and non-teaching hospitals. DesRoches et al. (2010) analyzed whether teaching status impacted adoption rates. They found that major teaching hospitals were more likely to have a system implemented, while non-teaching hospitals were more likely not to have implemented one. Adler-Milstein et al. (2015) used teaching status (major, minor, and non-teaching) as a variable in their study on hospital efficiency. Lee et al. (2015) used teaching affiliation as one of their hospital characteristics. Houser et al. (2011) also investigated teaching status when researching hospitals in Alabama. Furukawa (2011), Poon et al. (2004) and Bardhan and Thouin (2013) used teaching status as a hospital characteristic because teaching hospitals would have more access to advanced resources. Jha et al. (2009) conducted a study that found teaching hospitals were more likely to have EMR systems. In our study, we will see if teaching hospital status and EMR implementation impact hospital efficiency.

Hypothesis 4 (H4): Teaching hospital status and EMR implementation status may impact hospital efficiency.

2.5 Effect of ownership status and EMR on efficiency

We hypothesised that ownership status of the hospital could impact hospital efficiency. Different types of ownership status includes State/Local Government, Non-Profit and For-Profit. The different ownership types could impact which characteristics a hospital prioritises. For example, Bardhan and Thouin (2013) found that for-profit hospitals reported significantly lower operational expenses than non-profit hospitals. Houser investigated ownership status when researching hospitals in Alabama. Adler-Milstein et al. (2015) and Lee et al. (2015) also used ownership status as one of his hospital characteristics. In determining how much of an impact EMRs had on the workload of physicians, Bae and Encinosa (2016) looked at ownership type. DesRoches et al. (2010) analyzed whether the ownership type of the hospitals influenced adoption rates. They found for-profit hospitals were less likely to have a system implemented, while non-profit hospitals were more likely to have fully implemented systems. Jha et al. (2009) used ownership status as a factor in their study. Thus, we hypothesised that ownership status and EMR implementation status would impact hospital efficiency.

Hypothesis 5a (H5a): Government ownership and EMR implementation status would make an impact on hospital efficiency.

Hypothesis 5b (H5b): For-profit ownership and EMR implementation status would make an impact on hospital efficiency.

2.6 Effect of region and EMR on efficiency

We wanted to see if a hospital's region significantly impacted EMR implementation status and efficiency. When determining what factors could impact a patient's length of stay (LOS), Lee et al. (2015) considered geographic region of the hospitals as an option. Bae and Encinosa (2016) also heavily considered hospital region. They divided US into the following regions: Northeast, Midwest, South, and West. In their results, the South was the most likely region not to have implemented EMR systems. The Northeast was most likely to EMR systems implemented, with only 18.2% of hospitals not having one. Furukawa (2011) also looked into hospital region and found hospitals in the Midwest region were more likely to have fully functional EMR systems. In the data collected by DesRoches et al. (2013), they also found that hospitals in the South were less likely to have systems implemented. Whereas, Northeast hospitals were more likely to have basic systems, and Midwest hospitals were more likely to have fully comprehensive systems. Jha et al. (2009) also categorised results of the study using hospital region. In our study, we will analyze how much of an impact region can have. We hypothesise that region and EMR implementation status may impact hospital efficiency.

Hypothesis 6 (H6): Region and EMR implementation status may make an impact on hospital efficiency.

3 Model development

This study uses sample data from the American Hospital Association's 2015 Annual Survey of Hospitals. This voluntary survey was mailed to 6,300 hospitals that the American Hospital Association identifies as open and operating. Eighty percent of hospitals completed the surveys and mailed them back to the American Hospital Association. The purpose of the survey was to collect information about utilisation, finances and personnel. Survey data includes hospitals report information on their organisational structure, service lines, utilisation, finances, insurance and payment models, and staffing for a specific fiscal year as well as IT indicators i.e., EHR/EMR adoption, evolution of new care systems, community health partnerships, physician arrangements, and so on.

3.1 Input variable: number of beds

Cho et al. (2018) used DEA to calculate the efficiency of hospitals using four input measures, one being number of beds. Jha et al. (2009) observed that, of all the hospitals included in the survey, large hospitals implemented a fuller EMR system compared to small or medium hospitals. Small hospitals comprised the majority of those with no EMR systems. DesRoches et al. (2013) found that 61.9% of large hospitals have implemented either a basic or comprehensive EMR system. The study also found that the 46.6% of medium hospitals and 38.3% of small hospitals have implemented EMR systems. Kazley and Ozcan (2008) found a relationship between EMR use and efficiency for small hospitals, but not for medium or large hospitals. One possibility is that physicians spend more time documenting using EMR systems and that this could have caused efficiency to decrease.

In the 2015 AHA hospital survey data, the variable BDTOT measured the total facility beds set up and staffed at the end of the reporting period. We chose BDTOT in the proposed DEA model for an input to measure the total hospital beds in order to measure the size of the hospital.

3.2 Input variable: number of physicians

Cho et al. (2018) used DEA to calculate the efficiency of hospitals using the number of FTEs. Yasunaga et al. (2008) showed that the time efficiency of physicians was 25.8% with EMRs and 24.2% without an EMR system. Bae and Encinosa (2016) mentioned that with younger physicians, EMR use correlates with patient volume decline. Alternatively, EMR use among older physicians correlates with patient volume increase. If younger physicians behaved like older physicians when adopting EMR in their hospitals, this would result in an additional 37,600 weekly patient visits. This is the equivalent of adding 500 full-time physicians to the hospital workforce in US. In the 2015, AHA hospital survey data, the variable FTEMD measured the number of full-time physicians and dentists in each hospital. We chose FTEMD variable as an input to measure the full-time doctors in the proposed DEA model. In this, we aimed to measure the relative efficiency of a hospital.

3.3 Input variable: number of registered nurses

Cho et al. (2018) used DEA to calculate the efficiency of hospitals using number of FTEs as input. Yasunaga et al. (2008) showed that the time efficiency of nurses was 65.4% with EMRs and 47.7% without EMR systems. In the 2015 AHA hospital survey data, the variable FTERN measured the number of full-time registered nurses in each hospital. We chose the variable FTERN as an input to measure the full-time nurses in the proposed DEA model and to measure the relative efficiency of a hospital.

3.4 Input variable: operating expenses

Cho et al. (2018) used DEA to calculate the efficiency of hospitals using non-labour expenses as input. Hillestad et al. (2005) related hospital adoption costs to size and operating expenses of hospitals. Adler-Milstein et al. (2015) predicted that EMR adoption may result in improved efficiency because it could enable a reduction in both personnel and non-personnel expenses, particularly those related to medical records management. Kazley and Ozcan (2008) used operating expenses as an input to measure the efficiency of hospitals. This measures the degree to which inputs are being used to produce the best possible outcomes. In the 2015 American Hospital Association hospital survey data, the variable TOE measured the total operating expenses. We chose TOE in the proposed DEA model for an input to measure the operating expenses of the hospitals.

3.5 Output variable: number of outpatients

Kazley and Ozcan (2008) used the number of outpatients as an output to measure the efficiency of hospitals. Cho et al. (2018) used DEA to calculate the efficiency of hospitals using two output measures, one being outpatient visits. Hillestad et al. (2005) mentioned that a hospital could realise an estimated $10.6 billion a year in total outpatient savings by implementing an EMR system.

In the 2015 American Hospital Association hospital survey data, the variable VTOT measured the number of total outpatient visits. We chose VTOT in the proposed DEA model for an output to measure the outpatients at the hospitals.

3.6 Output variable: number of inpatients

Kazley and Ozcan (2008) mentioned that healthcare organisations have limited control over some of their outputs such as inpatient days because they are complex factors that are dependent upon supply and demand, as well as clinical entities. Hillestad et al. (2005) mentioned a hospital could realise $31.2 billion a year in total inpatient savings by implementing an EMR system. In the 2015 AHA hospital survey data, the variable IPDTOT measured the number of total facility inpatient days. We chose IPDTOT in the proposed DEA model for an output to measure the inpatients at the hospitals.

3.7 Output variable: operating revenue

Bardhan and Thouin (2013) mentioned that EMR usage correlates with a reduction in patient mortality rates and greater hospital productivity measured as revenue generated per admission. Houser et al. (2011) noted that a perceived benefit of EMR implementation in all hospitals is an increase of revenue. Thirty one percent of responses from hospitals in this study affirm this. Cherry et al. (2011) mentioned that none of the facilities in their sample provided financial data. However, those who discussed return on investment mentioned how they benefited positively in regard to revenue by implementing an EMR system. In the 2015 AHA hospital survey data, the variable TPR measured the total patient revenue for each hospital. We chose TPR in the proposed DEA model as an output to measure the revenue of the hospitals.

3.8 Control variable: electronic medical record implementation status

Yasunaga et al. (2008) showed that hospitals with EMR systems performed better than those without EMR systems in the following areas: time efficiency of physicians, time efficiency of nurses, time efficiency of testing, time efficiency of pharmaceutical services, information sharing among healthcare workers, inter-hospital networks, prevention of medical malpractice, space-saving, and use for medical research. Joos et al. (2006) stated that EMR implementation in a primary care practice correlates with perceived improvements in speed and communication efficiency and in information synthesis capabilities. Mao and Sun (2017) mentioned that the implementation of EMR systems could help hospitals to mitigate the increasing cost of healthcare. Kazley and Ozcan (2008) mentioned that EMR implementation may initially reduce efficiency as staff adjusts to new practices associated with EMR use, but hypothesised that hospitals with EMRs would increase in efficiency more than hospitals without EMRs. DesRoches et al. (2010) noted that implementing an EMR would not improve processes in a hospital automatically. Health institutions need to implement policies that change how employees work and that provide reasons to use the system. Once institutions have identified the improvements EMRs can make, employees would be more likely to use them efficiently. Furukawa (2011) determined that hospitals with fully functional EMR systems had significantly lower LOS compared to EMRs with lesser sophistication. Overall, EMR systems with higher levels of sophistication correspond with lower lengths of stays and reduced treatment times.

In the AHA survey, one question asked, “Does your hospital have an electronic medical record?” The study recorded responses in a variable named EHLTH, in which 0 = no, 1 = partial, 2 = fully implemented. We adopted EHLTH as a variable to measure the status of EMR implementation and used it to control the effect of inputs and outputs. For instance, EHLTH variable grouped hospitals into three groups: Group 1 = hospitals with no EMR systems, Group 2 = hospitals with partial implementation of EMR systems and Group 3 = hospitals with full implementation of EMR systems.

3.9 Control variable: hospital location type

Cho et al. (2018) summarised that many studies have found that hospitals in high-income and urban areas are more capable of implementing EMR systems than those in rural low-income areas are. Houser et al. (2011) stated that 12% of hospitals in Alabama indicated having implemented EMRs. Of those hospitals, fewer rural hospitals (8%) have implemented EMRs as compared with urban hospitals (18%). Jha et al. (2009) observed that hospitals in urban areas implemented full EMR systems more often compared to hospitals in non-urban areas. DesRoches et al. (2013) found that 47.7% of hospitals in rural areas have implemented either basic or comprehensive EMR systems. The study also found that the 33.5% of hospitals in urban areas have implemented EMR systems.

In the 2015 AHA hospital survey data, the variable CBSATYPE identifies the Core-Based Statistical Area Type for each hospital. The types could either be metropolitan, micropolitan or rural. We adopted CBSATYPE as a variable to measure the location type of the hospitals and to control the effect of inputs and outputs. For instance, CBSATYPE variable grouped the hospitals into three groups: Group 1 = hospitals in metropolitan areas, Group 2 = hospitals in micropolitan areas, Group 3 = hospitals in rural areas.

3.10 Control variable: teaching hospital

Houser et al. (2011) found that of the hospitals that have implemented an EMR system, 24% indicated that they had medical residency programs. Jha et al. (2009) observed that of all the hospitals included in the survey, teaching hospitals implemented full EMR systems more often compared to non-teaching hospitals. Bardhan and Thouin (2013) indicated that teaching hospitals exhibit greater operating expenses per bed. One may attribute this to the increased resource requirements associated with teaching hospitals. DesRoches et al. (2013) found that 68.8% of major teaching hospitals have implemented either basic or comprehensive EMR systems. The study also found that the 50.8% of minor teaching hospitals and 40.4% of non-teaching hospitals have implemented EMR systems.

In the 2015 AHA hospital survey data, the variable MAPP8 identifies whether each hospital is a member of Council of Teaching Hospital of the Association of American Medical Colleges (COTH). The data recorded responses in a variable named MAPP8, in which 1 = yes, 2 = no. We adopted MAPP8 as a variable to measure teaching hospital status and to control the effect of inputs and outputs. For instance, MAPP8 variable grouped the hospitals into two groups: Group 1 = teaching hospitals and Group 2 = non-teaching hospitals.

3.11 Control variable: ownership status

Jha et al. (2009) observed that private non-profit hospitals implemented full EMR systems more often than for-profit hospitals and public hospitals did. Bardhan and Thouin (2013) indicated that urban hospitals exhibit greater operating expenses per bed. One may attribute this to possible differences in staff pay and asset maintenance costs in urban locations. DesRoches et al. (2013) found that 49.6% of private non-profit hospitals have implemented either basic or comprehensive EMR systems. The study also found that the 39% of public hospitals and 29.8% of for-profit hospitals have implemented EMR systems.

In the 2015 AHA hospital survey data, the variable CNTRL identifies the control code of each hospital. The control code is the type of authority responsible for establishing policy concerning overall operation of the hospital. The types could either be government/non-federal, non-government/not-for-profit, investor-owned (for-profit), or government/federal. We adopted CNTRL as a variable to indicate the ownership status and used it to control the effect of inputs and outputs. For instance, CNTRL variable grouped the hospitals into four groups: Group 1 = government/non-federal owned hospitals, Group 2 = non-government/not-for-profit owned hospitals, Group 3 = investor-owned (for-profit) owned hospitals, and Group 4 = government/federal owned hospitals.

3.12 Control variable: region

Jha et al. (2009) observed that of all of the hospitals included in the survey, the hospitals in the Northeast had implemented EMR systems more often compared to the rest. They were followed by hospitals in the West, then hospitals in the South, and lastly hospitals in the Midwest. DesRoches et al. (2013) found that 49.1% of hospitals in the Midwest have implemented either a basic or comprehensive EMR system. The study also found that the 46.2% of the hospitals in the West, 44.4% of hospitals in the Northeast, and 38.7% of hospitals in the South have implemented EMR systems. Bae and Encinosa (2016) showed that of hospitals with EMR systems, 15.9% were in the Northeast, 23.6% in the Midwest, 30.4% in the South, and 30.1% in the West. Also, of hospitals without EMR systems, 18.2% were in the Northeast, 26.9% in the Midwest, 33.0% in the South, and 21.9% in the West. In the 2015 AHA hospital survey data, the variable REG measured the AHA region code. We adopted REG as a variable to indicate the region of each hospital and used it to control the effect of inputs and outputs.

3.13 Model specification

We employ data envelopment analysis (DEA) for measuring the relative efficiency of hospitals using electronic medical record systems. Many have completed research on the health service industry using DEA to measure the efficiency of health organisations (i.e., hospitals). DEA allows for the comparison of similar institutions based on the same inputs and outputs (Kazley and Ozcan, 2008). DEA is a special application of linear programming based on the frontier methodology of Farrell (1957). Since Farrell's work, the studies by Charnes et al. (1978) and Banker et al. (1984) achieved a major breakthrough for developing DEA. An entity that is an object measured for efficiency is called a decision-making unit or DMU. Because DEA identifies relatively efficient DMU(s) among a group of given DMUs, it is a promising tool for comparative analysis or benchmarking (Mhatre et al., 2014).

To explore the mathematical property of DEA, let E_0 be an efficiency score for the base DMU *0* then,

$$\text{Maximise} \quad E_0 = \frac{\left\{\sum_{r-1}^{R} u_{r0} y_{r0}\right\}}{\left\{\sum_{i-1}^{I} v_{i0} x_{i0}\right\}} \tag{1}$$

$$\text{subject to} \quad \frac{\left\{\sum_{r-1}^{R} u_{r0} y_{rk}\right\}}{\left\{\sum_{i-1}^{I} v_{i0} x_{ik}\right\}} \leq 1 \quad \text{for all } k \tag{2}$$

$$u_{r0}, v_{i0} \geq \delta \quad \text{for all } r, i, \tag{3}$$

where

y_{rk}: the observed quantity of output r generated by unit $k = 1, 2, \ldots, N$,

x_{ik}: the observed quantity of input i consumed by unit $k = 1, 2, \ldots, N$,

u_{r0}: the weight to be computed given to output r by the base unit 0,

v_{i0}: the weight to be computed given to input i by the base unit 0,

d: a very small positive number.

One can convert the fractional programming model to a common linear programming (LP) model without much difficulty. A major assumption of LP is a linear relationship among variables. Accordingly, an ordinary LP for solving DEA utilises a constant returns-to-scale so that all observed production combinations can be scaled up or down proportionally (Charnes et al., 1978). However, when we use a piecewise LP, we can model a non-proportional returns-to-scale such as an increasing, decreasing or variable-returns-to-scale (Banker et al., 1984). Depending on returns-to-scales and/or various modelling approaches, different types of DEA models are available.

Sherman and Ladino (1995) summarise the capability of DEA in the following manner:

- Identifies the best practice DMU that uses the least resources to provide its products or services at or above the quality standard of other DMUs.
- Compares the less efficient DMUs to the best practice DMU.
- Identifies the amount of excess resources used by the less efficient DMUs.
- Identifies the amount of excess capacity or ability to increase outputs for less efficient DMUs, without requiring added resources.

This study employs a Charnes-Cooper-Rhodes (CCR) model-based bilateral DEA model involving comparative measures of operational efficiencies for DMUs (Cooper et al., 2007). The inputs of the model in this study are number of hospital beds, operating expenses, number of physician FTEs, and number of registered nurse FTEs. The outputs are operating revenue, operating margin, number of outpatient visits and number of inpatient visits.

4 Results

Table 1 shows the descriptive statistics of our data. We divided the data into two groups: group 1 represents hospitals with no EMR implementation, and group 2 represents hospitals with partial or full EMR implementation. Table 2 shows the descriptive statistics of group 1 and 2. Table 3 shows the results of Pearson Correlation analysis in our data. Based on the results, the number of beds set up and staffed (BDTOT) is the most closely related to number of inpatient days (IPBDOT) with a correlation of 0.974049. The next most correlated variables are full-time equivalent registered nurses (FTERN) and total operating expenses (TOE) with a correlation of 0.943657.

Additionally, FTERN correlates highly with total patient revenue (TPR) with a correlation of 0.918553 as well as IPDTOT with a correlation of 0.916109. Overall, these inputs and outputs correlate highly with each other.

Table 1 Input and output variables

Variables		*Acronym*	*Min*	*Max*	*Mean*	*Std. Dev.*
Input	Number of Beds	BDTOT	3	2,654	195.2	232.99
	Number of Physicians	FTEMD	1	2,415	47.33	140.55
	Number of Registered Nurses	FTERN	4	6,905	375.89	572.52
	Operating Expenses	TOE	$2,724,118	$4,722,292,567	$236,099,336.70	$375,537,377.40
Output	Number of Outpatients	VTOT	64	713,946	46,781.60	63,366.07
	Number of Inpatients	IPDTOT	16	5,633,024	205,629.57	299,123.17
	Operating Revenue	TPR	$1,976,973	$14,143,533,186	$759,319,804.40	$1,255,323,483.00

4.1 Hypothesis testing results

A CCR-based bilateral DEA model computed relative efficiency scores of hospitals in the dataset, using DEA-Solver-Pro 13 software (Saitech, 2016). The DEA model results show that group 2 has a higher average efficiency score (0.9177 ± 0.5414) than Group 1 (0.5986 ± 0.2204) on average. We employed Mann-Whitney Test to test the first hypothesis. The results show statistical significance on the difference between two groups. Evidence shows that hospitals with either partial or full EMR implementation are more efficient than hospitals without EMR implementation. Thus, data supports Hypothesis 1. Table 4 summarises the test results on Hypothesis 1.

In the literature reviews, others observed that EMR implementations could yield numerous benefits towards healthcare organisations. Adler-Milstein et al. (2015) found that as EMR systems became more integrated, patient satisfaction and hospital performance increased. Additionally, both Lee et al. (2015) and Furukawa (2011) observed decreases in patient LOS in hospitals that had successfully implemented EMR systems. Accordingly, we hypothesised that hospitals with EMR systems are more efficient than hospitals without such systems. Our results confirmed the first hypothesis and corresponded with past literature showing that EMR implementation increases hospital efficiency.

Because control variables related to the remaining hypotheses (H2–H6) involved more than two groups, we used Kruskal-Wallis Test for hypothesis testing. Table 5 illustrates the coding information for the variables, and Table 6 describes the hypothesis test results.

Table 2 Input and output variables descriptions of Group 1 and 2

	Group 1 (No EMR Implementation)				*Group 2 (EMR Implementation)*			
	Max	*Min*	*Mean*	*Std. Dev.*	*Max*	*Min*	*Mean*	*Std. Dev.*
BDTOT	780	3	119.49	144	2,651	4	197.08	234.54
FTEMD	41	1	6.38	7.71	2,415	1	48.35	142.17
FTERN	1,384	7	105.57	209.4	6,905	4	382.62	577.2
TOE	$916,580,301	$3,889,568	$63,337,280	$136,751,636	$4,722,292,567	$2,724,118	$240,398,101	$378,664,892
IPBTOT	275,485	351	31,881.75	45,941.33	713,946	64	47,152.35	63,717.24
VTOT	336,979	989	44,085.66	63,837.22	5,688,024	16	209,649.21	301,626.85
TPR	$6,041,262,640	$5,114,440	$234,700,832	$837,545,168	$14,143,533,186	$1,976,973.00	$772,373,704	$1,261,606,580

Table 3 Correlation results of variables

	BDTOT	*FTEMD*	*FTERN*	*TOE*	*IPDTOT*	*VTOT*	*TPR*
BDTOT	1.0000	0.4279	0.9011***	0.8433**	0.9740***	0.6631*	0.8424**
FTEMD		1.0000	0.5857*	0.6692*	0.4677	0.5981*	0.5679*
FTERN			1.0000	0.9437***	0.9161	0.7534**	0.9186***
TOE				1.0000	0.8658	0.7862**	0.9233***
IPDTOT					1.0000	0.6745*	0.8598**
VTOT						1.0000	0.6931
TPR							1.0000

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Table 4 DEA analysis results

E Score	*Overall*	*Group 1*	*Group 2*
Number of DMUs	2183	53	2,130
Min	0.1175	0.1175	0.2211
Max	11.8210	1.1240	11.8210
Mean	0.9100	0.5986	0.9177
Std. Dev.	0.5382	0.2204	0.5414
M-W Statistics		6.9781	
p-value		0.0000	

We hypothesised that hospital size may have an impact on hospital efficiency. We conducted a non-parametric testing to see what impact bed size had. Results showed that in both group 1 and group 2, hospitals of 500 beds or more had the highest efficiency compared to the other sizes. We concluded that hospital size does impact hospital efficiency. Data supports Hypothesis 2.

Jha et al. (2009), Eberth and Thomas (2017), DesRoches et al. (2010), Cho et al. (2008), and Furukawa (2011) found that hospital location impacted hospital efficiency. We hypothesised that hospital location may impact hospital efficiency. Through Kruskal-Wallis non-parametric testing, we found similar results for both group 1 and group 2. The results showed that in both groups, metropolitan hospitals had the highest efficiency compared to the other two areas. The second highest efficiency location area was the micropolitan area. Therefore, location type does impact hospital efficiency. Data supports Hypothesis 3.

Based on the literature from several studies (DesRoches et al., 2010; Jha et al., 2009; Houser et al., 2011), we hypothesised that a teaching hospital that has an EMR system implemented would be more efficient than a non-teaching hospital without an EMR system implemented. We believed that teaching hospitals would be more likely to have access to advanced resources that would assist with increasing overall hospital efficiency. Among group 1, the teaching status did not matter ($p < 0.10$), while group 2 showed statistical significance ($p < 0.01$). Accordingly, teaching hospitals are more efficient than non-teaching hospitals among hospitals with EMR system implementation. Therefore, data partially supports Hypothesis 4. Teaching status impacts hospital efficiency among hospitals with EMR implementation.

Table 5 Variables and Mann-Whitney test results

Variables	*Levels (Code)*	*Definition*	*Group 1 (No EMR)* *Efficiency* *n*	*Mean*	*SD*	*Group 2 (EMR)* *Efficiency* *n*	*Mean*	*SD*	*Mann-Whitney Statistics*	*Z*	*p-value*
Hospital size	1	6–24 beds	7	0.4307	0.2807	189	0.8362	0.8402	340.0	–2.182	0.029
	2	25–49 beds	12	0.4488	0.1679	450	0.8861	0.7257	707.0	–4.366	<0.001
	3	50–99 beds	9	0.6467	0.1172	345	0.8837	0.3665	703.0	–2.803	0.005
	4	100–199 beds	18	0.6915	0.1767	414	0.8964	0.2610	2033.0	–3.265	0.001
	5	200–299 beds	4	0.7385	0.2789	262	0.9485	0.3342	281.0	–1.591	0.112
	6	300–399 beds	1	0.4840	NA	179	0.9820	0.5898	1.0	–1.703	0.022
	7	400–499 beds	0	NA	NA	92	0.9758	0.3995	NA	NA	NA
	8	500 ore more beds	2	0.8097	0.3057	199	1.0444	0.5878	152.0	–0.574	0.590
Location	1	Rural	8	0.3110	0.1287	489	0.8287	0.7072	168.0	–4.438	<0.001
	2	Micropolitan	9	0.4805	0.2121	411	0.8607	0.4487	529.0	–3.666	<0.001
	3	Metropolitan	36	0.6920	0.1687	1230	0.9721	0.4848	9656	–5.774	<0.001
Teaching status	1	Teaching hospital	1	1.0258	NA	177	1.0616	0.6236	49.0	–0.769	0.562
	2	Non-teaching hospital	52	0.5904	0.2163	1953	0.9046	0.5317	22297.0	–6.912	<0.001
Government status	1	Governmental institution	7	0.3455	0.1244	489	0.8408	0.6471	213.0	–3.980	<0.001
	2	Non-governmental institution	46	0.6371	0.2089	1641	0.9406	0.5037	16491.0	–6.522	<0.001
Profit status	1	For-profit organisation	29	0.6930	0.1980	170	0.9489	0.3437	1390.0	–3.750	<0.001
	2	Non-profit organisation	24	0.4845	0.1983	1960	0.9150	0.5553	5179.0	–6.575	<0.001
Region	1	West	7	0.5166	0.1697	315	0.8776	0.3917	282.0	–3.368	<0.001
	2	Midwest	18	0.5078	0.2302	771	0.8984	0.6731	2454.0	–4.692	<0.001
	3	Northeast	6	0.7459	0.1929	368	1.006	0.3532	503.0	–2.288	0.022
	4	South	22	0.6587	0.2080	676	0.9099	0.5132	4249.0	–3.424	<0.001

Bardhan and Thouin (2013), Furukawa (2011) and DesRoches et al. (2010) found that ownership status impact overall hospital efficiency. Therefore, we hypothesised that ownership status of the hospital may impact hospital efficiency. We split this hypothesis into two parts for the non-parametric hypothesis testing: government ownership status and profit ownership status. For government ownership status, both group 1 ($p < 0.01$) and group 2 ($p < 0.01$) showed statistical significance. Our study showed that in both groups, hospitals with and without EMR systems, non-governmental institutions had higher efficiency than governmental institutions. Therefore, government ownership status does impact hospital efficiency. Data supports Hypothesis 5a.

Table 6 Kruskal-Wallis test results

	Group 1 (No EMR Implementation)					*Group 2 (EMR Implementation)*				
	N = 53					*N = 2,130*				
Variables	*Level*	*Mean ranks*	χ^2	*d.f*	*p*	*Level*	*Mean ranks*	χ^2	*d.f*	*p*
Hospital size	1	36.43	15.8	6	0.015	1	1399.90	161.1	7	< 0.001
	2	37.92				2	1231.59			
	3	24.11				3	1106.69			
	4	19.67				4	1008.21			
	5	20.50				5	941.50			
	6	40.00				6	932.78			
	7	0				7	867.54			
	8	14.00				8	794.28			
Location area	1	45.88	20.5	1	< 0.001	1	1319.50	156.72	1	< 0.001
	2	35.33				2	1172.64			
	3	20.72				3	928.72			
Teaching status	1	2.00	2.7	1	0.102	1	778.73	41.97	1	< 0.001
	2	27.48				2	1091.48			
Government status	1	44.14	9.9	1	0.002	1	1258.63	62.59	1	< 0.001
	2	24.39				2	1007.95			
Profit status	1	20.03	13.0	1	< 0.001	1	963.65	5.07	1	< 0.001
	2	35.42				2	1074.33			
Region	1	33.43	7.809	3	0.050	1	1113.34	95.86	3	< 0.001
	2	32.78				2	1152.58			
	3	16.83				3	784.62			
	4	23.00				4	1096.79			

For profit ownership status, both group 1 ($p < 0.01$) and group 2 ($p = 0.02$) reported the statistical significance. Our study showed that in both group 1 and group 2, for-profit organisations had higher efficiency than non-profit organisations, on average. Therefore, profit ownership status does impact hospital efficiency. Data supports Hypothesis 5b.

We were interested in determining whether the location of a hospital and its EMR implementation status would influence a hospital's efficiency. We hypothesised that region and EMR implementation status did impact a hospital's efficiency. Both group 1 ($p = 0.05$) and group 2 ($p < 0.01$) show statistical significance. We found that hospitals in the Northeast are more efficient, regardless of whether they implement EMR systems. Evidence supports Hypothesis 6. Therefore, we can determine that region impacts overall hospital efficiency.

4.2 Managerial implications

This study benefits healthcare executives by providing data that indicates whether implementing an electronic medical records system improves a hospital's efficiency.

Collecting data from hospitals that the American Hospitals Association recognises provides managers with reliable data from hospitals across the country and allows them to compare their hospital to others. They can compare the variables of their hospitals with those of this study to determine the implications for their hospitals. Implementing an EMR system is extremely costly, so knowing if it improved efficiency for similar institutions is essential. With healthcare costs expected to reach $1.8 trillion by 2026, being able to provide reliable data to prove that the implementation costs associated with an EMR system is worth it in the long run benefits healthcare overall. This allows managers to make informed decisions when deciding whether their hospitals should implement EMR systems. The study concludes that hospitals with EMR systems implemented are more efficient than hospitals without EMR systems implemented. In addition, it will be helpful to scale up the size of a hospital to increase its efficiency.

5 Conclusion

The major contribution of this study is in its confirmation of the benefits of implementing EMR systems in hospitals across US. Because EMR systems are costly, it is important to highlight the benefits that these systems provide to hospitals, specifically in the area of hospital efficiency. Hospital management can use this information to decide if the benefits of EMR implementation outweigh the costs depending on a hospital's location (rural, metropolitan, micropolitan), teaching hospital status, ownership status (government vs. non-government and for-profit vs. non-profit), and region (West, Northeast, South, Midwest). This information can lead to more efficient hospitals in US.

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