Does Electronic Health Record Systems Implementation Impact Hospital Efficiency, Profitability, and Quality?

C. Christopher Lee
Central Connecticut State University

Youngseon Kim
Central Connecticut State University

Jeong Hoon Choi
University of Nebraska Kearney

Ethan Porter
Lake Superior State University

This paper empirically analyzed how electronic health records (EHR) systems impacted hospital operations. This study examined the merits of implementing EHR in operational efficiency, profitability, and service quality delivered to patients. Therefore, this research tested three hypotheses postulating overall positive associations of EHR implementation for the three areas, respectively. This paper used the 2015 American Hospital Association U. S. Hospital Survey dataset and the Hospital Consumer Assessment of Healthcare Providers and Systems dataset. To measure each hospital's efficiency, this study developed a data envelopment analysis model with four inputs including beds, doctors, nurses, and total operating expenses, and three outputs including outpatient visits, inpatient days, and total patient revenues. This research used the operating margin to measure the hospital profitability, while patient experience ratings and readmission rates were used to measure the hospital quality. Results indicated that EHR implementing hospitals outperformed non-EHR implementing hospitals in operational efficiency, profitability, and quality.

Keywords: electronic health records systems, data envelopment analysis, hospital efficiency, profitability, quality

INTRODUCTION

President Obama signed the Affordable Care Act (ACA) into law in March 2010 (Patient Protection and Affordable Care Act). Since the enacting of the ACA, U.S. hospitals have implemented Electronic Health Records (EHR) systems. EHRs have gained a reputation as the modern storage method of health information and have begun replacing paper records. EHRs effectively store health records and provide valuable information to medical providers at service (Williams et al., 2010). The American Recovery and

Reinvestment Act of 2009 (ARRA), also signed by President Obama, included the Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009, incentivizing meaningful use of EHRs. In this act, the U.S. Congress included a formula for both incentives for EHR adoption and penalties for the continued use of paper records. The government required compliance with these mandates as of 2014. Since then, hospitals in the U.S. have worked on implementing EHR systems.

This research examines the relationship between the implementation of EHRs and hospital efficiency, profitability, and quality. Three major research questions are: (1) If a hospital utilizes an EHR system, will the hospital become more efficient? (2) If a hospital utilizes an EHR system, will the hospital become more profitable? (3) If a hospital utilizes an EHR system, will the hospital deliver better quality service? We primarily use data obtained from the hospitals participating in the American Hospital Association (AHA) Annual Survey Database for Fiscal Year 2015. This source is a comprehensive hospital database for health service research and market analysis and has been available since 1946. This research supplements survey responses with data from the American Hospital Association registration database, the U.S. Census Bureau, hospital accrediting bodies, and other organizations.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Research on the implementation and usage of EHRs in hospitals shows that EHRs benefit the ease and agility of recovering patient information and provide better controls over prescriptions (Cortes & Cortes, 2009). The increased adoption of EHRs in the U.S. and other countries has led to a dramatic growth of clinical data available in electronic format. It significantly has reduced medical errors in daily hospital operations (Jindal & Raziuddin, 2016). Legible communication, cost savings, streamlined data flow, and the ability to report and examine patient data are all high priorities that EHRs improve, according to Gunter et al. (2005). Many researchers have examined potential areas in which EHR can improve hospital operations, but few studies have researched the relationship of EHRs to hospital efficiency, profitability, and quality together. A literature review of past studies shows a lack of research on this topic. We intend to examine whether the implementation of EHRs will help hospitals improve operational efficiency, profitability, and the quality of care that they deliver to patients. We believe that this research will expand our knowledge regarding the value of EHR implementations by filling the gap in research related to EHR systems. Next, we present each of the critical variables in the current research and our hypotheses.

Efficiency is an important measure when evaluating hospital operations. Zhivan and Diana (2011) indicated that the more inefficient a hospital was, the more likely it would be to adopt an EHR system because the benefits far outweigh the costs. Reversely put, we can infer that EHR systems would improve efficiency in hospital operations. Menachemi and Collum (2011) showed that clinical, societal, and organizational benefits of EHR led to improved efficiency across several categories. EHR implementation resulted in higher vaccination rates due to computerized reminders, increased revenue, averted costs, and an improved ability to conduct research due to having patient data available electronically. One hundred medical professionals in Arizona demonstrated that EHR systems helped reduce medical errors. Such error reduction led to better patient care and greater patient satisfaction (Jindal & Raziuddin, 2016). We hypothesize that EHR implementation has a positive correlation with hospital efficiency.

Hypothesis 1: *There is a positive relationship between adopting an EHR system and increasing hospital efficiency.*

Hospital administrators have a significant interest in profitability. Improving profitability will be a decisive factor when deciding whether to adopt EHR. Furukawa et al. (2010) estimated the effects of EHR implementation on medical-surgical acute unit costs, length of stay, nurse staffing levels, nurse skill level, nurse cost per hour, and patient outcomes. They found that EHR implementation accounted for a 6-10% higher cost per discharge in acute units and a 15-26% increase in daily nurse hours per patient. They also found that EHR usage reduced the nurse cost per hour by 2-4% and reduced in-hospital mortality by 3-4%.

In short, these findings linked the contribution of EHRs to cost savings and elevated profitability. We hypothesize that implementing EHR will improve profitability.

Hypothesis 2: *There is a positive relationship between the adoption of EHR systems and hospital profitability.*

Quality of patient care is a significant concern for hospital administrators. A fundamental aspect of efficiency analysis studies on any health care organization maintains that sacrificing the quality of care will not achieve efficiency or profitability gains (Choi & Oh, 2018). If health care organizations do not consider the quality of patient care, the health care unit will be more productive simply because the unit operates at a lower quality level. Medical mistakes are a major concern for the health care industry. Hospitals demand ongoing efforts to minimize errors and improve the quality of care for patients.

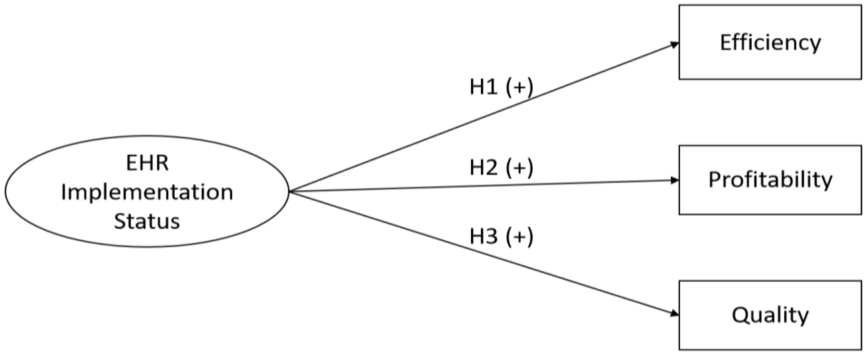
Scientists have implemented efforts to prevent compromised patient safety through the combined use of available innovations, such as nanomedicine and EHR systems (Jindal & Raziuddin, 2016). Furukawa et al. (2010) examined the influence of EHR implementation on nurse staffing and patient outcomes using data from the California Office of Statewide Health Planning and Development from 1998 to 2007. This longitudinal study discovered that EHR reduced nursing costs per hour by 2 - 4% and reduced in-hospital mortality by 3 - 4%. However, DesRochers et al. (2010) concluded that the relationship between EHR and predicted quality was not significant. Anderson et al. (2018) showed that interprofessional communication and collaboration could improve patient outcomes. Systematic educational reviews and EHR communication tools may improve patient and system outcomes for intensive care units with early mobility program patients. Jindal and Raziuddin (2016) concluded that EHR systems appear to offer substantive advantages over paper records for containing costs and improving the quality of care.

In addition, Parente and McCullough (2009) found that the use of EHR had a small yet positive effect on overall patient safety. They determined that healthcare institutions should make additional investments into healthcare I.T. to improve patient safety further. McCullough et al. (2010) found that the average quality of patient care improved in hospitals with implemented EHRs by 1-2% in six different quality categories. Jindal and Raziuddin (2016) concluded that EHRs lead to a reduction in medical errors. Lee et al. (2013) found that hospitals that adopted EHR had 0.11 day shorter length of stay, a 0.182% lower 30-day mortality rate, and a 0.19% increase in the 30-day rehospitalization rate. Menachemi and Collum (2011) suggested that an EHR system would eliminate many billing errors or inaccurate coding. It could increase a provider's cash flow and enhance revenue by reducing outstanding days in accounts receivable and lost or disallowable charges. EHR reminders to providers and patients about routine health visits can increase patient visits, increasing revenue. Considering this, we hypothesize that EHR implementation will help improve the quality of patient care.

Hypothesis 3: *There is a positive relationship between EHR implementation and the quality of patient care in hospitals.*

Figure 1 depicts the research framework. This framework illustrates the impact of EHR implementation on hospital efficiency, profitability, and quality of care.

FIGURE 1
RESEARCH FRAMEWORK



METHODOLOGY

Data Envelopment Analysis Model

We employed a data envelopment analysis (DEA) model to measure the comparative efficiencies of the implementation of EHRs and hospital efficiency (H1). DEA is a special application of linear programming based on the frontier methodology of Farrell (1957). It is useful for detecting relative efficiency among similar organizations or objects. An entity to be measured for efficiency is called a decision-making unit (or DMU). A DEA model identifies relatively efficient DMU(s) among a group of given DMUs and conducts comparative analysis or benchmarking.

To explore the mathematical property of a basic DEA model, let E_0 be an efficiency score for the base DMU_0. Then, Mhatre, Joo, and Lee (2014) describes the objective function and constraints of a general DEA model as follows:

Maximize

$$E_0 = \frac{\{\sum_{r=1}^{R} u_{r0} y_{r0}\}}{\{\sum_{i=1}^{I} v_{i0} x_{i0}\}} \tag{1}$$

subject to

$$\frac{\{\sum_{r=1}^{R} u_{r0} y_{rk}\}}{\{\sum_{i=1}^{I} v_{i0} x_{ik}\}} \leq 1 \qquad \text{for all } k \tag{2}$$

$$u_r, v_{ib} \geq \delta \qquad \text{for all } r, i \tag{3}$$

where:

$y_{xk} =$ the observed quantity of output r generated by unit $k = 1,2, \dots, N$.
$x_{ik} =$ the observed quantity of input i generated by unit $k = 1,2, \dots, N$.
$u_{r0} =$ the weight to be computed given to output r generated by the base unit 0 .
$v_{i0} =$ the weight to be computed given to input i generated by the base unit 0 .
$\delta =$ a very small positive number.

One needs to carefully identify input and output variables because of the industry's non-profit nature and the complexity of care services. The following section briefly introduces the variables included in our data analysis.

Input Variables for Hospital Efficiency

We selected four input variables to examine the effect of EHRs on hospital operations. These variables include the number of beds (BDTOT), the number of full-time equivalent physicians and dentists (FTEMD), the number of full-time equivalent registered nurses (FTERN), and total operating expenses (TOE). *BDTOT* variable represents the total facility beds set up and staffed at the end of the reporting period (Green, 2002). *FTERN* variable represents the number of full-time registered nurses on-site at a hospital at the end of the reporting period (Tucker & Spear, 2006).

Output Variables for Hospital Efficiency

We chose the output variables in our model from the dataset. These are the number of outpatients' visits (VTOT), total facility inpatient days (IPDTOT), and total patient revenue (TPR). *VTOT* variable, taken directly from the data set, represents total outpatient visits during the entire reporting period for the given hospital (Cheng et al., 2008). *TPR* variable represents the sum of total inpatient revenues and total outpatient revenues for the total reporting period of 2015 for the given hospital (Bank et al., 2013).

Profitability Variable

We selected operating margins as a quantifiable metric to measure a hospital's profitability. This measure of profitability indicates how much of each dollar of revenue remains after deducting costs of goods sold and operating expenses. It is calculated by dividing operations earnings by revenues.

Quality Variables

We adopted two measures for the quality variables from the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) database. The survey result of HCAHPS provides a standardized survey instrument and data collection methodology for measuring patients' perspectives on hospital care. The first quality variable is the readmission rate. Medicare collected this data from 1,631 hospitals (Medicare, 2019). Another measure we adopted from the HCAHPS database is the national comparison of patient experience measures. It has three response categories, "Below the national average," "Same as the national average," and "Above the national average," which are coded 1, 2, and 3, respectively. Medicare collected this data from 1,589 hospitals (Medicare, 2019).

Control Variable

AHA dataset classified the hospitals (EHLTH) into three groups (Group 1= hospitals with no EHR, Group 2 = hospitals with partial implementation, and Group 3 = hospitals with full implementation). We also used EHLTH as a control variable to control its effect on inputs and outputs. In addition, we created EHLTH_1 by re-coding the variable EHLTH and included it as another control variable. We dichotomized three groups of EHR implementation levels. No EHR hospitals received a 1, meaning lack of EHR implementation. Those with partial implementation or full implementation received a 2, indicating some engagement in EHR.

RESULTS

Data Collection

This research used a dataset from the 2015 American Hospital Association Annual Survey. The AHA had a voluntary response rate to its survey nearing 80%. Using regression models and a matrix of estimators, the AHA estimated and filled in any missing values or records for hospitals that did not respond (American Hospital Association, 2017). The dataset initially included responses from 6,251 hospitals operating within the United States.

To ensure accurate results, we cleaned the data before performing our analysis. We removed 2,228 hospitals with blank values for the EHLTH (Status of EHR implementation) grouping variable (n = 3,964). Then, we moved on to the input variables. FTEMD (Number of full-time equivalent physicians and dentists) had no blank values. However, there were 1,561 hospitals with a reported value of "0". We subsequently removed those cases (n = 2,403). TOE (the total facility expenses) had one hospital reporting a negative value and 94 hospitals reporting a 0, #N/A, or blank. We removed these 95 abnormal cases (n=2,308). The values for the other input variables were valid with no missing data or zeros.

As per our output variables, VTOT (Total facility inpatient days) had 95 hospitals reporting a "0" value. We removed all of these from our analysis. TPR (Total patient revenues) had 30 hospitals reporting a "0" value. We also removed these. The values for the other output variables were all valid with no blank data or zeros, leaving us a final sample size of 2,183. We imported a readmission rate variable and a patient experience variable as quality measures from Medicaid data provided in a separate file. We had valid data for 600 records that we performed additional analysis on separately.

Descriptive Statistics

Table 1 shows the input and output variables and their descriptive statistics without considering whether the hospital uses EHR systems.

TABLE 1
DESCRIPTIVE STATISTICS ON INPUT AND OUTPUT VARIABLES

	BDTOT	FTEMD	FTERN	TOE	IPDTOT	VTOT	TPR
Max	2,654	2,415	6,905	4,722,292,567	713,946	5,633,024	14,143,533,186
Min	3	1	4	2,724,118	64	16	1,976,973
Average	195.2	47.3	375.9	236,099,337	46,781.6	205,629	759,319,804.4
SD	233.0	140.6	572.5	375,537,377	63,366.1	299,123	1,255,323,483

Note: Input variables include BDTOT (Bed Total), FTEMD (Number of full-time equivalent physicians and dentists), FTERN (Number of full-time equivalent registered nurses), and TOE (Total Operating Expenses), while output variables include IPDTOT (Total Facility Inpatient days), VTOT (Number of Outpatient visits), and TPR (Total Patient Revenue). SD = Standard Deviation

Table 2 presents descriptive statistics of the hospital group without EHR implemented. All the averages of the input variables (BDTOT, FTEMD, FTERN, TOE) in Group 1 are below those of all hospitals. FTEMD, FTERN, and TOE are substantially lower. Output variables (IPDTOT, VTOT, TPR) also show the same pattern. VTOT and TPR are substantially lower.

TABLE 2
DESCRIPTIVE STATISTICS ON GROUP 1 (NO EHR IMPLEMENTATION)

	BDTOT	FTEMD	FTERN	TOE	IPDTOT	VTOT	TPR
Mean	119.5	6.4	105.6	63,337,279.8	31,881.8	44,085.7	234,700,831.9
Median	90.0	4.0	43.0	21,699,144.0	20,861.0	17,784.0	47,688,372.0
SD	144.0	7.7	209.4	136,751,635.	45,941.3	63,837.2	837,545,168.4
Minimum	3.0	1.0	7.0	3,889,568.0	351.0	989.0	5,114,440.0
Maximu	780.0	41.0	1,384.0	916,580,301.0	275,485.0	336,979.0	6,041,262,640.0
Count	53.0	53.0	53.0	53.0	53.0	53.0	53.0

Table 3 shows the descriptive statistics regarding the hospitals that implemented EHR either partially or fully. All the averages of the input variables (BDTOT, FTEMD, FTERN, TOE) in Group 2 are slightly higher than those of all hospitals. Output variables (IPDTOT, VTOT, TPR) also show the same pattern.

TABLE 3
DESCRIPTIVE STATISTICS ON GROUP 2 (PARTIAL OR FULL EHR IMPLEMENTED)

	BDTOT	FTEMD	FTERN	TOE	IPDTOT	VTOT	TPR
Mean	197.1	48.4	382.6	240,398,110.9	47,152.4	209,649.2	772,373,703.7
Median	114.0	11.0	162.0	99,601,627.0	23,962.5	111,715.5	282,254,586.0
SD	234.5	142.2	577.2	378,664,891.6	63,717.2	301,626.9	1,261,606,579.9
Minimum	4.0	1.0	4.0	2,724,118.0	64.0	16.0	1,976,973.0
Max	2,654.0	2,415.0	6,905.0	4,722,292,567.0	713,946.0	5,633,024.0	14,143,533,186.0
Count	2,130.0	2,130.0	2,130.0	2,130.0	2,130.0	2,130.0	2,130.0

Correlation Analysis

We ran a correlation analysis with all the input and output variables. Our first input, BDTOT (Bed total), had the highest correlation with the input IPDTOT (Number of inpatient days) at 97.4%. The correlation is high because the amount of beds determines the capacity of patients a hospital can take at one time. BDTOT has the lowest correlation with the input FTEMD (Number of full-time equivalent physicians and dentists). FTEMD's highest correlation is 66.92% with the input TOE (Total operating expenses). This makes sense as operating costs will increase with each full-time employee added. The third input FTERN (Full-time equivalent registered nurses) predictably correlated with BDTOT at 90.11%, input TOE at 94.37%, IPDTOT at 91.16%, and TPR at 91.86%. The fourth input, TOE, also correlated with the output TPR at 92.33%. The output VTOT (Total Facility Inpatient days) did not have a high correlation with any other variables. Their correlation ranged from 66.31% with the input FTEMD to 78.62% with the input TOE.

TABLE 4
CORRELATION MATRIX OF INPUT AND OUTPUT VARIABLES

	BDTOT	FTEMD	FTERN	TOE	IPDTOT	VTOT	TPR
BDTOT	1						
FTEMD	0.427862	1					
FTERN	0.901138	0.585708	1				
TOE	0.843341	0.669171	0.943657	1			
IPDTOT	0.974049	0.467654	0.916109	0.865828	1		
VTOT	0.663074	0.598053	0.753403	0.786249	0.674482	1	
TPR	0.847243	0.567900	0.918553	0.923333	0.859770	0.693071	1

Benchmarks

Table 5 presents the profiles of the top 10% of the DMUs that we will regard as our benchmarks. These DMUs were 220 hospitals that received the highest efficiency score measurements in the DEA model. They all belonged to Group 2 (Partial or Full EHR Implementation). The average number of beds in one of these hospitals (BDTOT) was 664. The average FTE doctors and dentists (FTEMD) was 231.2 doctors. The average FTE registered nurses (FTERN) was 1,627.5. The average total operating expenses in the top 10% hospital was $1,047,641,988. The average inpatient days (IPDTOT), outpatients (VTOT), and total patient revenue (TPR) were 176,601 days, 681,910 patients, and $3,606,253,188, respectively.

Numerous previous studies have measured the performance of hospitals using efficiency scores. The frontier approach frequently has been applied in such research to measure the efficiency of health care organizations. It constructs unobservable production or cost frontiers and estimates inefficiencies by measuring the distances of observations from the frontier. The frontier approach is divided mainly into the stochastic frontier analysis (SFA), a parametric approach, and data envelopment analysis (DEA), a non-parametric and mathematical method. Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977) initially introduced SFA as a form of the production function to estimate productive inefficiency. The SFA method uses a parametric estimation and assesses efficiency by decomposing the error term into managerial inefficiency and other conventional noise (Aigner et al., 1977; Jondrow et al., 1982). By taking into account the stochastic property of the data, the SFA alleviates the drawbacks of the DEA and measures the efficiency of entities such as countries (Lin 2009), manufacturing firms (Lin & Chuang 2013), and retail stores (Gauri, 2013; Ratchford & Stoops, 1988). However, the SFA is limited to only one output variable with the product or cost, which is suitable for measuring the efficiency of the traditional production function in the manufacturing industry.

TABLE 5
DESCRIPTIVE STATISTICS OF TOP 10% EFFICIENT HOSPITALS

	BDTOT	FTEMD	FTERN	TOE	IPDTOT	VTOT	TPR
Mean	664.1	231.2	1,627.5	1,047,641,988.2	176,601.0	681,910.5	3,606,253,188.3
Median	607.5	89.0	1,413.0	878,363,879.0	160,513.5	487,918.0	2,862,081,162.0
SD	352.5	371.0	934.0	645,389,843.0	94,823.6	598,537.2	2,046,032,438.4
Minimum	30.0	1.0	292.0	253,580,739.0	9,889.0	83,062.0	2,070,503,414.0
Maximum	2,654.0	2,415.0	6,905.0	4,722,292,567.0	713,946.0	5,633,024.0	14,143,533,186.0
Count	220.0	220.0	220.0	220.0	220.0	220.0	220.0

Testing Hypothesis 1

Hypothesis 1 tests a positive relationship between utilization of EHR and hospital efficiency. We compared the efficiency scores among two groups of hospitals, those with no EHR implementation and those with EHR implementation. The average efficiency score of hospitals without EHR was 0.5986 compared to the average efficiency score of the hospitals with implemented EHR of 0.9177. The difference between the two groups is meaningful ($p < 0.05$). Therefore, data supported H1 - Hospitals with EHR implemented tend to be more efficient than those without EHR. For detailed results, see Table 6.

TABLE 6
HYPOTHESIS 1 TESTING RESULTS

	N	Average	SD	Rank Sum	Rank Mean	M.W. Statistic$^{\#}$
Group 1	53	0.5986	0.2204	89,506	1,688.7900	6.9781***
Group 2	2130	0.9177	0.5414	2,294,330	1,077.1502	
Total	2183	0.9090	0.5382			

$^{***}p < .001$; $^{\#}$Mann-Whitney Test Statistics

Testing Hypothesis 2

To test the second hypothesis, we performed a one-way ANOVA test. Our independent variable was EHR implementation. We used operating margin as our dependent variable to measure the impact the EHR system could have. The status of the EHR implementation was divided into three groups, no EHR (0), a partial implementation (1), or a complete implementation (2). After running a homogeneity test of variances and the Welch test, we yielded results that supported our hypothesis. The results showed a statistically significant difference in operating margins between hospitals with partial implementation and those with fully implemented EHR systems. Finally, hospitals with fully implemented EHRs (EHR Group 2) had the highest mean operating margin, or in this case, the lowest net loss of -3.576 ± 30.317, compared to EHR Group 0 (-4.407 ± 34.588) and EHR Group 1 (-11.692 ± 83.679).

One assumption of the one-way ANOVA test is that all comparison groups have the same variances. If they are not equal, it can cause the *F*-statistic to be biased. Subsequently, this can lead one falsely to reject the null hypothesis. We ran a test of homogeneity of variances to verify the results of our ANOVA. The test showed that data distributions of the three groups differed significantly [*Leven statistic* (2, 3770) = 19.284, $p = 0.000$]. Because of this, we ran the Welch robust test of equality of means instead of the ANOVA model. The Welch test modifies the degrees of freedom to increase the test power for samples with unequal variances, such as ours. Welch statistic is based on the asymptotical F distribution. The results showed that our three groups differed significantly [*Welch statistic* (2, 469.612) = 3.511, $p = 0.031$]. Evidence showed that hospital profitability decreased substantially when hospitals partially implemented EHR (-11.6924 ± 83.6786). Once hospitals fully implemented EHR, they achieved the highest profitability (-3.5762 ± 30.317341). Table 7-1 reports the Welch test results.

TABLE 7-1
WELCH ROBUST TEST OF EQUALITY OF MEANS FOR OPERATING MARGIN

EHR Implementation	N	Mean	SD	DF	Welch Statistic
No	203	-4.4073	34.5880	2,469.612	3.511*
Partial	760	-11.6924	83.6786		
Full	2,801	-3.5762	30.3173		
Total	3,773	-5.2751	46.7183		

* $p < 0.05$

Next, we compared the mean difference for each group for the post-hoc analysis. We used the Games-Howell Test. The test results in Table 7-2 show a significant difference in operating margin between hospitals with EHR partial implementation and hospitals with full implementation [Mean Difference = -8.116 ± 3.071, $p = 0.023$].

TABLE 7-2
GAMES-HOWELL TEST FOR POST-HOC ANALYSIS

EHR Implementation Comparison			Mean Difference	Standard Error	*p*-value
No	vs.	Partial	7.2852	3.87282	0.1450
No	vs.	Full	-0.8311	2.49427	0.9410
Partial	vs.	Full	-8.1163	3.07142	0.0230

In summary, data supported Hypothesis 2. Evidence showed that hospitals suffered from the financial loss during the partial EHR stage, on average; however, hospital profitability improved substantially from the partial to full EHR implementation stages. Once a hospital fully implemented EHR, it reached the highest level of profitability among the three stages.

Testing Hypothesis 3

H3 tests a positive association between EHR implementation and perceived quality delivered in hospitals. For this hypothesis testing, we used the readmission rate and the national comparison of patient experience as quality measures and EHLTH as the predictor variable. We analyzed 600 hospitals that reported their readmission rate. We included 2,067 hospitals with patient experience ratings separately for the analysis.

Our analysis showed that EHR implementation impacted the patient experience rating only ($p < .001$), not the readmission rate. According to the Tukey post hoc test, meaningful differences in patients' quality ratings existed between no EHR hospitals and fully EHR implemented hospitals ($p < .001$) and between no EHR hospitals and partially EHR implemented hospitals ($p < .01$), respectively. The difference was more significant in the former case. Evidence showed that the overall implementation of EHR in hospitals would significantly increase patients' rating of hospital service quality. The difference between the partially EHR implementing hospitals and fully EHR implementing hospitals was insignificant.

DISCUSSION

Our research examines the impact of EHR adoption on hospital operations, especially in efficiency, profitability, and quality delivered. We used the 2015 Annual AHA survey data and imported quality measures from the HCAHPS database available on the Medicare website. The research strongly supported all three hypotheses that we tested.

Hypothesis 1 examined the positive association of EHR implementation with operational efficiency in hospitals. The results align with Furukawa et al. (2010), which reported that EHR implementation would positively impact medical-surgical acute unit costs, length of stay, nurse staffing levels, and patient outcomes. The results follow general assumptions that the adoption of technology would improve lives on a daily basis and lead to greater operational efficiency in hospitals.

Hypothesis 2 proposed a positive relationship between EHR implementation and profitability. Data supported the hypothesis with a statistically significant difference. The results show that hospital profitability decreased substantially when hospitals implemented EHR partially. Once hospitals fully implemented EHR, they achieved the highest profitability. This result fully endorses former research findings (e.g., Lee et al., 2013; Menachemi & Collum, 2011).

Finally, in Hypothesis 3, we predicted that EHR implementation would enhance the quality of care delivered to patients. We used two separate variables as proxies for quality measures, readmission rate and national comparison of patient experience. The latter, more of a quality measure from the patient perspective, answers whether EHR implementation would help deliver quality service, which would lead to increased patient satisfaction and loyalty to the relevant hospitals. We confirmed that EHR implementation positively relates to patients' quality ratings. Whether they implemented EHR partially or fully, hospitals demonstrated higher scores in quality measures than those without EHR implementation. Thus, our results contradict the proposition by Furukawa et al. (2010) that EHR implementation had nothing to do with quality improvement in hospitals.

Managerial Implications

EHR helps make daily processing flow better and lowers the chance of human error. When it comes to operational efficiency and profitability, our research findings reinforce the practical applications of EHR. These applications to improve hospital efficiency and profitability will be countless. The current research also proves that hospitals with EHR (partially or fully implemented) deliver better quality than those with no EHR, as perceived by patients. This suggests that hospitals should adopt an EHR system from a managerial standpoint. Cortes and Cortes (2009) identified the ease and agility of information and better control over prescriptions, materials, and procedures as key benefits EHR brought to hospitals. Data shows that the implementation of EHR reduces medical errors and leads patients to perceive a hospital as higher quality (Jindal & Raziuddin, 2016). Our research findings provide hospital managers with legitimate reasons to implement EHR systems for their daily hospital operations.

CONCLUSION

Findings from our research strongly support the proposition that implementation of EHR will help hospitals improve operational efficiency, patients' perception of service quality, and profitability in the long run. However, we note that while we had 2,183 cases for testing our hypotheses using the DEA model, a reasonably large sample, the number of hospitals with no EHR implemented in the dataset is small. The hospitals with EHR implemented either partially (459 cases) or fully (1,671 cases) outnumbered the hospitals with no EHR (53 cases). The comparison of the operating margin as the outcome variable among three groups of hospitals could have been overshadowed by the dominance of hospitals with any level of

EHR implementation. The imbalance in the number of cases in each hospital category might have factored into our results. Future researchers could expand on our study by replicating our results using a dataset without such an imbalance of cases. Our research findings encourage hospitals to adopt and implement EHR in their daily operations. This paper is the first study to examine the relationship of EHRs to hospital efficiency, profitability, and quality together.

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