Does the Electronic Medical Record (EMR) Adoption Matter? Exploring Patterns of EMR Implementation and its Impact on Hospital Performance

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Abstract

We aimed to explore the patterns of electronic medical records (EMR) adoption and its effects on hospital performance. We analyzed hospital-level panel data from 2008 to 2013 using Bayesian regression and the Naïve Bayes model. Our research analysis revealed 38 different adoption patterns for 1,919 hospitals that completed EMR implementation (having all of the four components) and 42 different adoption patterns for 1,341 hospitals that could not complete the EMR implementation. We examined the hospitals' EMR adoption patterns that were not completed; but predicted as completed using the Naïve Bayes model. Our results revealed that the hospitals that completed EMR adoption showed higher performance in terms of patient recommendation and net patient revenue than those that did not complete EMR adoption. More importantly, most of hospitals that observed as "not completed" but predicted as "completed" showed lower performance in terms of patient recommendation as well as net patient revenue.

Keywords: Healthcare Information Technology, Electronic Medical Records, Bayesian regression, Naïve Bayes model

1. Introduction

In 2009, the US government implemented the Health Information Technology for Economic and Clinical Health Act (HITECH) to promote the adoption of health information technologies (HIT) and improve the quality of care. In response to this act, hospitals started adopting diverse HIT, offering improved healthcare services. With the increase in adoption and use of HIT in healthcare, a better understanding of how to adopt and exploit IT to improve organizational performance in healthcare becomes an important consideration in the information systems (IS) field (Agarwal et al., 2010; Fichman et al., 2011; Kohli and Tan 2016; Lucas et al., 2013).

Given this emphasis on HIT, many scholars have been interested in attempting to discover whether there are any noticeable relationships between HIT adoption and hospital performance. Unfortunately, we found that there is a lack of effort to explore the variations in technology adoption behaviors at the hospital level. Except for a few papers, most previous technology adoption research in a hospital setting focused on whether technology adoption occurs or not and how a hospital allocates its budget to IT resources (e.g., Romanow et al., 2018; Oh et al., 2018; Wang et al., 2018). However, it is reasonable to believe that the tendency to adopt the EMR or HIT at any hospital may be unique or vary because every hospital faces its own different financial and economic environment. Even understanding technology adoption as a binary action (i.e., adoption or non-adoption) or quantity-based measures may limit the full understanding of the potential value of the HIT. Therefore, we argue that healthcare organizations or hospitals are likely to enforce distinct managerial strategies in technology adoption differently, yielding varied outcomes.

Accordingly, the goal of the current study is to discover whether there exist unique patterns of EMR technology adoption and identify its effects on hospital performance using the hospitals' EMR adoption records. Narrowing the scope of the investigation of EMR is crucial because it plays a particularly important role in explaining many managerial aspects of hospital sustainability and achieving patient satisfaction. The importance of studying EMR has also been acknowledged by prior studies across various disciplines (Hydari et al., 2019).

EMR is not a single technology but a bundle of several components. Usually, four components are considered as parts of EMR: (1) a clinical data repository (CDR); (2) a clinical decision support system (CDSS); (3) computerized provider order entry (CPOE); and (4) physician documentation (PD) (Atasoy et al., 2018; Dranove et al., 2014). Such recognizable functional features provide us with the rationale behind investigating the potentially different types of adoption of technology in each hospital. For example, some hospitals may adopt all of the

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components of EMR at once, while others may adopt individual components sequentially. Alternatively, some hospitals may not adopt all of the components, but rather only adopt some of them. Based on the arguments above, we raise the following research questions.

RQ1: Does the completion of EMR implementation influence hospital performance?
RQ2: Are there any specific EMR adoption patterns among hospitals? If so, do hospitals eventually complete the EMR implementation?
RQ3: Are there any performance differences between hospitals relating to their degree of EMR adoption completion?

Our paper contributes to the literature by enhancing understanding of EMR technology adoption behavior and its effects. As addressed above, prior studies have focused on examining HIT adoption, investment, or implementation from a holistic perspective. However, we argue that such an approach cannot capture the possible variations in HIT technology adoption behaviors and their potentially different results. To the best of our knowledge, only two prior studies investigated the sequential patterns of technology adoption in a hospital setting. Angst et al. (2011) investigated the order in which medical technologies, including nuclear cardiology, intravascular ultrasound, CT scanning, and echocardiology, are integrated into information systems and whether certain configurations of sequences of integration yield additional value. More recently, Spaulding et al (2013) explored the sequential patterns of health information systems, including clinical documents, computerized physician order entry, order communication and results, pharmacy information systems, automated dispensing machines, and electronic medication administration records. Although these studies provide useful insights into understanding technology adoption behavior, these studies employed a theory-driven approach, which resulted in missed opportunities to uncover more diverse patterns using actual adoption data (Maass et al., 2018). Our paper fills these gaps by exploring more diverse adoption patterns using a merged dataset.

The following sections review prior studies regarding EMR adoption and describe the research method. Discussions and implications are then addressed.

2. Literature Review

2.1 Electronic Medical Records

Numerous health IT systems contribute to the overall enhancement of care quality and health performance. In particular, Electronic Medical Records (EMR) play a particularly important role in offering robust healthcare services; thus, they have been widely studied across various disciplines (Hydari et al., 2019). While there is little consensus on the components of EMR, CDR, CDSS, CPOE, and PD are widely accepted as parts of EMR (Atasoy et al., 2018; Dranove et al., 2014). A CDR is a database that is used to keep track of patient information, including demographics, clinical information, hospitalization history, billing, and so on. A CDSS aids health care providers with diagnosis and treatment plans by providing reference information and care recommendations. CPOE enables physicians to manage medical orders electronically, such as pharmaceutical, laboratory, and radiological orders. PD allows physicians to keep computerized records of their patients' medical conditions. Our research focused on the adoption of these four components at the hospital level, examining its impact on hospital performance and identifying the adoption variations among hospitals.

2.2 The Need to Examine Health Information Technology Adoption Patterns in Healthcare

Healthcare information technology has been adopted at various levels for a decade, in everything from simple, computerized workstations to comprehensive medical support systems.

Table 1. Summary of previous studies on HIT adoption

Agha (2014)	
Variables & theories	Medical expenditure, patient health, HIT implementation, adoption year, patient characteristics
Methods	Medicare Claims Data (Center for Medicare and Medicated Studies), HMICSS, AHA Annual Survey
Findings	No cost savings after adopting HIT, little impact on the quality of care in terms of patient mortality, adverse drug event and readmission rates.
Angst et al. (2011)	
Variables & theories	Interoperability (number & sequence), performance, maturity of IT, number of beds, location, year

Methods	Data collection from HIMSS, individual data from cardiology technology, AHD data. 555 hospitals
Findings	Sequence of integration yields value. Interoperable sequences outperform other sequences if implementing foundational IS earlier.
Bardhan and Thouin (2013)	
Variables & theories	Clinical IS, Financial systems, Scheduling systems, HR systems, Process care quality, Operating expense
Methods	Hospital IT usage data from Dorenfest Institute for HIT Research, US Department of HHS Hospital Compare Program, US Center for Medicare and Medicade Service.
Findings	A positive association between clinical IS use and patient scheduling application, and conformance with best practices for the treatment of heart attack/failure, and pneumonia.
Bhargava and Mishra (2014)	
Variables & theories	Physician productivity, IT productivity, task-technology fit.
Methods	Measuring physician's performance productivity – 3,189 observations from 87 physicians.
Findings	EMR systems do not produce the productivity gain and do not cause a major productivity loss on a sustained basis.
Colicchio et al. (2016)	
Variables & theories	Literature review
Methods	Descriptive screening of 236 studies to identify outcome measures used and the availability of data
Findings	Quality care, productivity, and patient safety are the most common categories that are used for the taxonomy of commonly used outcome measures.
Gardner et al. (2015)	
Variables & theories	HIT infrastructure, Strategic processing (SP), Error processing (EP), Care quality, Patient satisfaction
Methods	Primary data – hospital survey, secondary data – HIMSS (Dorenfest), HCAHPS/CMS
Findings	Significant relationship between EP and care quality, between SP and care quality. Significant relationship between EP and patient satisfaction. Significant interaction effect (EPXHIT) on care quality.
Hydari et al. (2019)	
Variables & theories	Patient safety events, basic EMR, advanced EMR, patient Days, County controls, Hospital controls, Year, Hospital fixed effects, Teaching-year fixed effect, Year fixed effect.
Methods	Difference-in-differences. Hospital longitudinal data – patient safety data.
Findings	Advanced EMR declines significantly patient safety events driven by reductions in medication errors, falls, and complication errors.
Karahanna et al. (2019)	
Variables & theories	Culture capital, social capital, economic capital, hospital digital advantage.
Methods	Data from HIMSS, AHA, AHD, CMS.
Findings	Significant direct relationship between hospital digital advantage and cultural/social/economic capital. Multiple interaction effects among economic/social capital hospital digital advantage.
Lin et al. (2019)	
Variables & theories	Meaningful use, Quality adoption, Patienthroughput, Medicareratio, Medicaid ratio, Casemix, Competition Intensity.
Methods	3-year hospital panel data
Findings	Positive effect of EHR on quality care, EHR benefits varied per different level of EHR use and hospital characteristics. Positive impact of meaningful use of EHR on societal benefit.

Earlier literature has studied HIT adoption in relation to patient outcomes, emphasizing the role of the patient and organizational heterogeneity (McCullough et al., 2016). That study collected hospital-level IT adoption data for five years and identified the effective role of HIT adoption in reducing the deaths of those who suffered from complex diseases. McKenna et al. (2018) identified the impact of HIT adoption on inpatient outcomes in New York State. The study revealed a significantly decreased rate of the severity-adjusted mortality rate for the hospital. Another study examined the impact of complementarity between clinical HIT and hospital-level performance measures using data from 716 hospitals (Mishra et al., 2022). The study examined HIT implementation, clinical and experiential qualities, and healthcare costs. The results showed that four aspects of complementarity (symbiotic, pooled, simultaneous, and sequential) influenced hospital quality and cost outcomes. Oh et al. (2018) revealed that the application of HIT is related to reducing the deviation between the length of stay (LOS) and the geometric mean of LOS using 4-year hospital-level data from heart failure patients. Pinsonneault et al. (2017) accessed records for 15,626 outpatients who received ambulatory care and found that integrated HIT had a significant direct and indirect effect on improving the quality of care, which integrated HIT-facilitated care among physicians, specialists, hospitals, and pharmacists. Another study categorized HIT into two HIT bundles – clinical HIT and augmented clinical HIT – depending on its functionalities in terms of simple information collection and the active integration of collected information with the capability of decision making

(Sharma et al., 2016). The authors found that both HITs complement each other in terms of conformance and experiential qualities.

As reviewed above, the HIT studies approached the functionalities impacting HIT performance, service qualities, economic impact, patient safety, quality care, and so on. Unlike that kind of holistic examination approach, our study focused on the HIT adoption patterns that prior studies have rarely been interested in.

3. Research Method

3.1 Data Description

As addressed above, we primarily focused on hospitals that adopted CDR, CDS, CPOE, and/or PD. We collected data from hospitals in the US between 2008 and 2013. Specifically, our study used the Healthcare Information and Management Systems Society (HIMSS) Analytics database to obtain data on patterns of practice in the adoption of CDR, CDS, CPOE, and PD by hospitals. These technologies are considered adopted in year *t* if it is categorized by HIMSS as "live and operational" in that year. Binary coding (0, 1) was used to indicate either adopted or not-adopted (Sharma et al., 2016). We also used the American Hospital Association (AHA) Annual Survey, the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) survey, and the Centers for Medicare and Medicaid Services (CMS) databases for outcome and control variables. Using Medicare IDs, we combined hospital data from the three databases.

3.2 Variable Description

Two hospital performance variables were used: net patient revenue; and willingness to recommend the hospital. The net patient revenue was calculated as the total patient revenue minus any allowances or discounts in the AHA patient accounts. The willingness to recommend a hospital was a survey result in the HCAHPS. This variable was measured as the percentage of patients who answered "Yes" to the question, "Would you recommend this hospital to your friends and family?" (Mishra et al., 2022)

Our study also employed several control variables to incorporate the differences in hospital characteristics into our research method. We controlled for hospital size (number of hospital beds), as size implies hospital-level differences in service capacity (Bradley et al., 2018). For location control variables, we used binary variables, indicating whether a hospital is located in a rural area or not. We further controlled for governmental ownership, the hospital's profit status, membership of affiliated healthcare networks, the hospital's teaching status, and medical school affiliation. Finally, we controlled for CMI, a composite measure reflecting the complexity and diversity of service procedures offered to patients (Brown et al., 2003). A higher level of CMI requires a hospital to allocate and deploy more resources (e.g., more suppliers and human resources) for service delivery (Angst et al., 2011; Sharma et al., 2016), which is likely to increase operating expenses (i.e., supply and personnel expenses) as well as affecting clinical outcomes.

4. Data Analysis & Results

To answer our research questions, we employed three statistical approaches as follows: (1) Bayesian Regression; (2) the Naïve Bayes Model; and (3) Expected Value. We first extracted EMR adoption patterns from our data set. Then, we compared the performance of hospitals adopting all components of EMR (complete EMR adoption) with those adopting some of the components or not adopting any components (incomplete EMR adoption). Lastly, we examined the expected performance of incomplete EMR adoption patterns. Detailed analysis results are discussed below.

4.1. EMR Adoption Patterns

To find EMR adoption patterns, we used two steps. First, we examined our data set and what EMR components are adopted per year manually. Then, we used the Naïve Bayes model to determine whether a hospital completed EMR adoption based on the observed adoption patterns.

We found a total of 80 adoption patterns of EMR adoption, which are the combination of the four EMR component adoptions over six years (Table 3). For example, ABCD indicates that a hospital adopts each of the four EMR components per year over six years, while O means that a hospital adopts all of the EMR components in one year within six years window between 2008 and 2013. Overall, during the time frame of our data set (2008 ~ 2013), 1,919 hospitals completed EMR adoption (i.e., adopted all components of EMR), showing 38 different patterns. In contrast, 1,341 hospitals could not complete the adoption of EMR (i.e., adopted only some EMR components), yielding 42 different adoption patterns.

Table 2. EMR adoption patterns

Pattern Type	Adopted Technology / Year
A	CDR
B	CDS
C	CPOE
D	PD
E	CDR, CDS
F	CDR, CPOE
G	CDR, PD
H	CDS, CPOE
I	CDS, PD
J	CPOE, PD
K	CDR, CDS, CPOE
L	CDR, CDS, PD
M	CDR, CPOE, PD
N	CDS, CPOE, PD
O	CDR, CDS, CPOE, PD
P	No Adoption
Note: Clinical data repository (CDR); Clinical Decision Support System (CDSS); Computerized Provider Order Entry (CPOE); Physician Documentation (PD)	

To better understand the implications of EMR adoption patterns, we used the Naïve Bayes model. The Naïve Bayes classifier is a simple probabilistic classifiers method based on the Bayes theorem described in the following equation:

$$p(A|B) = \frac{P(B|A)P(A)}{P(B)} \text{ (Basic Bayes Theorem)} \qquad (1)$$

In our case, the prediction of whether the EMR adoption would be completed or not should be A, while lots of different EMR component adoption patterns are denoted as B in equation (1). Therefore, the main assumption for our research would be each of the EMR component adoption decisions is independent each other.

According to Fisher's Separation Theorem in economics, given efficient capital markets, a firm's technology adoption choice is independent from its owners' preferences, and a firm should only be motivated to maximize its profits. Although the majority are not-for-profit in the US, financial soundness may be necessary for not-for-profit hospitals to continue operating hospitals. Therefore, the theorem gives us the theoretical support that the EMR adoption decisions in a specific hospital today should, in the same manner, depend on the hospital's profit maximization, not the types of EMR adoption made in the previous adoption term. Second, we assume that each EMR adoption pattern would bring unique benefits to a specific hospital; hence, each EMR adoption pattern should be equally important. Hence, the formal formula (1) should be denoted as:

$$p(y = EMR\ adt.completed\ or\ not \mid x = adoption\ patterns) \propto p(x_1|y)p(x_2|y)\ldots p(x_n|y)p(y) \qquad (2)$$

$$p(y = EMR\ adt.completed\ or\ not \mid x = adoption\ patterns) \propto p(y)\prod_{i=1}^{n} p(x_i|y) \qquad (3)$$

$$\therefore y = argmax_y\{p(y)\prod_{i=1}^{n} p(x_i|y)\} \qquad (4)$$

To build the Naïve Bayes classifier, we split the entire dataset into training and test datasets. We removed missing data from 22,053 cases and finally used 12,260 cases for the analysis. 9,000 cases are used as a training dataset to build a model, and 3,260 cases are used as a testing dataset to validate the model.

Our Naïve Bayes classifier predicts whether a hospital will complete EMR adoption (i.e., adopt all of the four components) or not, given the adoption patterns. For example, if a hospital's adoption pattern is E (i.e., adopt CDR and CDS), our Naïve Bayes model will predict whether this hospital will complete EMR adoption by additionally adopting CPOE and PD, given the adoption pattern E. Then, we compare the predicted (classified) values by our Naïve Bayes classifier with the observed values in the dataset. Through the comparison, we get the results (Figure 1). For instance, if our Naïve Bayes model predicts that a hospital will complete EMR adoption given an adoption pattern, but the hospital actually does not complete it, this is a false-positive case.

According to the results (see Figure 1), among 80 EMR adoption patterns (i.e., 35+3+20+22 patterns in Figure 1), 42 patterns (Area III + IV) are observed as "Not Completed", meaning that 1,341 hospitals' EMR adoption had not been completed. Meanwhile, based on the Naïve Bayes Model, 55 unique EMR adoption patterns (i.e., Area I + III; 35+20) are classified as "Completed adoption ". Therefore, we finally found 20 unique patterns (Area III), which were classified as "Completed adoption " yet were observed as " Adoption had not been completed."

	Classified as "Completed"	Classified as "Not Completed"
Observed as "Completed"	Area I. True Positive 35 Patterns 1,904 Hospital Cases	Area II. False Negative 3 Patterns 15 Hospital Cases
Observed as "Not Completed"	Area III. False Positive 20 Patterns 82 Hospital Cases	Area IV. True Negative 22 Patterns 1,259 Hospital Cases

Figure 1. Classification results based on Naïve Bayes

4.2. Effect of EMR Adoption Completion on Hospital Performance

Next, we compared two EMR adoption patterns: (1) adopting all components of EMR (complete EMR adoption); and (2) adopting some of the components or not adopting any components (incomplete EMR adoption). To estimate the relationship between the outcome variables and EMR adoption completion, we used the regression model with the Bayesian approach as follows:

$$y \sim N(\mu, \sigma^2) \text{ and } \mu = \alpha + \beta EMRComp + \gamma_i CV_i, where\ i = 1, \dots, 8 \quad (5)$$

where y denotes performance variables, assuming following the normal distribution, *EMRComp* is status of the EMR completion, and *CV* denotes control variables.

Equation (5) is a Bayesian regression model. It is assumed that the prior is Gaussian distribution. We estimated the equation by applying the Markov Chain Monte Carlo (MCMC) methods and a Metropolis-Hastings algorithm with a random walk chain. MCMC is a more precise analysis than ordinary regression analysis because of iterative simulations. Also, our final dataset for the analysis is about EMR adoption patterns appearing over the time frame (2008 - 2013). The final dataset has a cross-sectional nature, although the raw data has a panel structure. Thus, we employed the MCMC method instead of panel models.

We ran the MCMC chain for 15,000 iterations and used the last 13,000 iterations to compute the mean and standard deviation of the posterior distribution of the model parameters ($\alpha, \beta, \gamma_1, \dots, \gamma_8$). The results are in Tables 3 and 4.

Table 3. The Effect of complete EMR Adoption on patient recommendation

	DV: patient Recommendation					
	Mean	ESS	HDI Mass	HDI Low	HDI High	Sig
Constant	74.59	13859	.99	73.36	75.83	***
EMR Compl.	.489	15000	.99	.06	.933	***
Hospital Size	-.005	12503	.99	-.01	-.003	***
Fed. Gov.	.915	15000	.90	-4.39	5.871	
For Profits	-2.72	14581	.99	-3.319	-2.141	***
Under System	-.427	14697	.95	-.810	-.063	**
Medical Affiln	-.255	14633	.90	-.622	.072	
Teaching	-.587	13778	.90	-1.152	-.012	*
Urban	-.076	14448	.90	-.408	.274	
CMI	7.81	13653	.99	6.878	8.774	***
Note: ***p < 0.01; **p < 0.05; *p < 0.1; ESS (Explained Sum of Square); Highest Density Interval (HDI); Case Mix Indexes (CMI)						

According to the results, the completion of EMR adoption increases patient recommendations from patients by 0.489 points, which is statistically significant. This finding indicates that hospitals completing EMR adoption can expect to get 75.079 points for recommendations from patients. However, hospitals not completing EMR adoption would expect to get 74.59 points for patient recommendations.

Table 4. The effect of complete EMR adoption on net patient revenue

	DV: Net Patient Revenue					
	Mean	ESS	HDI Mass	HDI Low	HDI High	Sig.
Constant	-84M	12977	.99	-96M	-71.00	***
HIT Inv. Compl.	5.7M	15000	.99	1.4M	10.0 M	***
# Bed	.9M	7846	.99	.9M	1M	***
Fed. Gov.	-45M	14624	.90	-90M	2.5M	
For Profits	-24M	14264	.99	-29M	-19M	***
Under System	1.9M	14597	.90	-1.1M	5.1M	
Medical Affiln	17M	14470	.99	11M	24M	***
Teaching	151M	12408	.99	125M	177M	***
Urban	1M	12851	.90	-2.2M	3.9M	
CMI	66M	11972	.99	55M	76M	***
Note: ***p < 0.01; **p < 0.05; *p < 0.1; ESS (Explained Sum of Square); Highest Density Interval (HDI); Case Mix Indexes (CMI)						

The results show that hospitals that implement the adoption of EMR expect to get \$5.7 million more in net patient revenue than the others. This is statistically valid because the Highest Density Interval (HDI) Mass is .99.

Overall, these results imply that hospitals need to complete EMR adoption. However, we can find hospitals that do not complete EMR adoption despite being expected to complete EMR adoption by the Naïve Bayes classifier (Figure 1). Thus, we focused on these cases and examined their performance.

4.3. Examining Incomplete EMR Adoption Patterns

To gain more insight into the relationships between EMR adoption patterns and hospital performance, we compared the expected performances of 82 hospitals as false-positive cases in Area III in Figure 1 (classified as "completed", but actually observed as "Not Completed"). These 82 hospitals only make up 2.5% of our entire study. However, it is inevitably damaging to local health welfare if such hospitals perform badly. Therefore, understanding these partial subjects is important.

Tables 5 and 6 compare expected patient recommendations and the expected net revenue of 82 hospitals (20 patterns) and two benchmarks. Each benchmark represents either (1) immediate additional EMR adoption cases (e.g., AB → ABC and so on) or (2) all complete cases. For example, the first case, benchmark 1, compares one of the 20 patterns (e.g., adoption D case) to other adoption cases such as DB, DC, DE, or DK case. If we do not find some benchmark (1) case, then we denoted N/A. The second comparison case compares each of the 20 patterns to other completed adoption cases. Finally, we marked each of the 20 adoption patterns as *lower*, *mixed*, and *higher* depending on the comparison results. For example, we marked it as *lower* when the expected value of each of the 20 patterns was lower than benchmarks 1 and 2. By the same logic, we marked it as higher when the expected value of each of the 20 patterns was higher than benchmarks 1 and 2, and we marked it as mixed when the expected value of each of the 20 patterns was lower than one of the benchmarks while it was higher than the other.

According to the results, 74 subjects out of 82 false positive hospitals were lower than the two benchmarks. These results imply that false-positive cases are underperforming; hence, the hospitals classified as false positive need to invest in at least one more technology or move to true-positive cases by completing their EMR adoption.

Table 5. Comparison of avg. recommendation to benchmark

Patte-rns	E.V. of Recom-mendations	Bench-mark 1	EV of Benchm-ark1	E.V. of Benchm-ark2	Compar-ed to Benchm-arks
ABD	78.75	ABDC	86.39	84.54	Lower
ADB	67.34	ADBC	N/A	84.54	Lower
AI	**85.55**	**AIC**	**83.85**	**84.54**	**Higher**
AJ	82.79	AJB	82.52	84.54	Mixed
BAD	82.24	BADC	83.93	84.54	Lower
BCA	83.00	BCAD	N/A	84.54	Lower
BCD	82.34	BCDA	N/A	84.54	Lower
BG	86.50	BGC	87.11	84.54	Mixed
BJ	82.53	BJA	N/A	84.54	Lower
CBA	81.93	CBAD	N/A	84.54	Lower
D	80.11	DB	85.81	84.54	Lower
	80.11	DC	85.43	84.54	Lower
	80.11	DE	83.59	84.54	Lower
	80.11	DK	85.71	84.54	Lower
DE	82.81	DEC	83.90	84.54	Lower
ED	83.05	EDC	83.63	84.54	Lower
F	82.00	FB	84.52	84.54	Lower
	82.00	FI	84.05	84.54	Lower
FB	83.54	FBD	84.97	84.54	Lower
GB	83.63	GBC	84.77	84.54	Lower
GC	75.00	GCB	N/A	84.54	Lower
I	75.00	IA	81.15	84.54	Lower
	75.00	IF	86.83	84.54	Lower
IA	**87.66**	**IAC**	**78.99**	**84.54**	**Higher**
N	**88.47**	**NA**	**86.09**	**84.54**	**Higher**

Table 6. Comparison of avg. net patient Revenue to Benchmarks

Patte-rns	E.V. of Net Rev.	Bench-mark 1	EV of Benchm-ark1	E.V. of Benchm-ark2	Compar-ed to Benchm-arks
ABD	77.4M	ABDC	416.5M	245.0M	Lower
ADB	171.0M	ADBC	N/A	245.0M	Lower
AI	60.7M	AIC	222.6M	245.0M	Lower
AJ	47.2M	AJB	300.8M	245.0M	Lower
BAD	94.3M	BADC	139.6M	245.0M	Lower
BCA	162.0M	BCAD	N/A	245.0M	Lower
BCD	123.5M	BCDA	N/A	245.0M	Lower
BG	**423M**	**BGC**	**145.3M**	**245.0M**	**Higher**
BJ	29.9M	BJA	N/A	245.0M	Lower
CBA	42.4M	CBAD	N/A	245.0M	Lower
D	238.3M	DB	442.4M	245.0M	Lower
	238.3M	DC	144.8M	245.0M	Mixed
	238.3M	DE	224.7M	245.0M	Mixed
	238.3M	DK	333.4M	245.0M	Lower
DE	53.3M	DEC	293.3M	245.0M	Lower
ED	145.6M	EDC	223.0M	245.0M	Lower
F	110.9M	FB	329.6M	245.0M	Lower
	110.9M	FI	338.8M	245.0M	Lower
FB	194.6M	FBD	392.6M	245.0M	Lower
GB	135.5M	GBC	253.0M	245.0M	Lower
GC	95.9M	GCB	N/A	245.0M	Lower
I	85.3M	IA	110.7M	245.0M	Lower
	85.3M	IF	316.4M	245.0M	Lower
IA	**317M**	**IAC**	**42.0M**	**245.0M**	**Higher**
N	13.0M	NA	267.2M	245.0M	Lower

However, we did find some interesting cases of IA, BG, AI, and N patterns. First, in the case of the IA pattern, both the average recommendation and average net revenue per year are higher than the benchmarks. Based on the results in Tables 5 and 6, adopting CDS and PD first and then CDR could be a logical decision for some hospitals. However, we only studied one hospital that has this pattern. Hence, we cannot formally conclude that adoption pattern of IA is better than IAC or completed adoption.

Second, we found that the BG case has higher expected net patient revenue than its benchmarks. Therefore, the adoption pattern BG - adopting CDS first and then CDR, and PD - sounds logical. However, we also only have one hospital case for BG adoption.

Finally, we saw eight hospitals adopting the AI and N patterns. These eight hospitals have higher recommendations, but lower expected net patient revenue compared to their benchmarks. In these cases, we found huge gaps in net patient revenue among the adoption patterns and their benchmarks, but only small differences in their recommendations. Therefore, in the long run, hospitals may be better off investing further in CDR, then CDS and PD together, or CDS, CPOE, and PD together.

5. Discussion and Implications

This study explored EMR adoption patterns and their effects on hospital performance. To do so, we used Bayesian Regression and the Naïve Bayes Model. We found 80 unique adoption patterns in hospital information technology. Over six years, between 2008 and 2013, 1,919 hospitals completed the EMR adoption with 38 different patterns. In contrast, 1,341 hospitals completed partial adoption in EMR components, and there are 42 different EMR component adoption patterns for those 1,341 hospitals. Our research categorized EMR adoption patterns using adoption information from 3,260 hospitals between 2008 and 2013. Our results revealed that the completion of EMR adoption statistically significantly influences patient recommendations and net patient revenue. We also examined 82 hospitals that did not complete EMR adoption but classified as completed EMR adoption in more detail by comparing them with two benchmarks: 1) cases that completed the next adoption immediately; and 2) cases that completed the EMR adoption.

Our results showed that most of the 82 hospitals recorded lower patient recommendations and net patient revenue as hospital performances, compared to the two benchmarks. While there is evidence that these 20 adoption patterns caused a lack of hospital performance, we also found some interesting cases in which incomplete EMR adoption patterns revealed higher performance than the two benchmarks. For example, in terms of patient recommendations, the AI, IA, and N patterns showed higher patient recommendation values than the two benchmarks. In addition to the IA pattern, the BG pattern also showed a higher net revenue value than the two benchmarks.

Overall, our paper enhances our understanding of technology adoption behavior and its effects by providing meaningful insights and implications. For example, unlike prior studies, we empirically showed that hospitals' EMR adoption has diverse patterns. More importantly, some hospitals did not complete the EMR adoption even though they were expected to complete it. Furthermore, incomplete adoption worsens hospital performances compared to other hospitals that complete all EMR components and even to the hospitals that implement one more EMR module. In practical terms, such findings provide insight into how to plan HIT implementation, what to consider, and why HIT adoption is crucial for healthcare practitioners, given extensive historical data.

6. Research Limitations and Future Research

Our research has some limitations. First, as a preliminary study, we only examined false-positive cases and patterns in which cases were observed as not completed but were, in fact, classified as completed. Thus, future research needs to delve into other cases to fully understand EMR adoption behaviors.

Also, we focus on showing different EMR component adoption patterns and their performance. We did not provide possible explanations for hospitals that did not complete their adoption in EMR components even though statistical results clearly show that completed adoption outperforms incomplete ones. Specifically, we did not provide explanations for the 82 hospitals that are classified as EMR complete adoption but not completed. However, previous studies considered many factors as impediments to EMR adoption. For example, Razmak et al. (2018) argued that physician support, hospital management support, and governmental incentives are related to innovative technologies adoption in a hospital setting. According to the recent qualitative study by van Poelgeest et al. (2021), medical specialists considered their relationships with patients, technical knowledge, and the time taken to implement EMR systems as significant barriers for EMR adoption. Thus, it would be important research to explain why hospitals did not complete their adoption of EMR components. It is because such future studies may provide theoretical and practical explanations of inevitably damaged local health welfare because of poor investment decisions of hospitals.

Also, we did not consider the time taken to adopt EMR. Previous studies argued that it would take time to reap the benefits after adopting technologies. (Jasperson et al., 2005; Zhang and Venkatesh, 2017). Thus, the performance could be different depending on when EMR adoption is completed.

In addition, in section 4.3, we compared the performances (patient recommendations and net revenue) of false-positive hospital cases to their benchmarks without statistical analysis (e.g., t-test). It is because we have only a few cases in each pattern (e.g., only one hospital of patterns ADB, AJ, BCA, BCD, BG, CBA, I, & IA), making it hard to compute statistical analysis. Hence, future research could replicate our methods and compare the sub-samples (false positive) to their benchmarks when data may be cumulated.

Lastly, we include controls following previous studies. However, there may be other factors that is linked to adoption decisions. For example, market factors (e.g., competition) may affect hospitals' decisions on technology adoption. Thus, future studies need to include more control variables.

Even with such limitations, this study contributes literature in several ways. First, our research provides a new possible research stream for the hospital EMR adoption and their performance. Also, we clearly answer the research questions: (1) the relationship between EMR adoption, and performances, (2) different EMR component investment patterns, and (3) performance comparisons of some hospital examples of long tail and their benchmarks.

7. References

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