Technology implementation, experience and hospital focus – A longitudinal analysis of electronic medical records in acute care hospitals

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ABSTRACT

Drawing on the theoretical framework of resource-based view of the firm and the operations management concept of "focused factory", this study examines the performance impacts of the stage of EMR implementation and the associated post EMR-adoption experience. We postulate a nuanced perspective of the impact of technology by examining whether these impacts differ across hospitals with varying levels of focus, defined as the level to which a hospital's operations are concentrated in certain clinical areas. Based on our analysis , we observe several interesting findings: (1) lower EMR stages are mainly associated with improved hospital operational performance while higher EMR stages have greater positive effects on care quality and patient satisfaction, (2) EMR experience has significant positive impacts on both operational performance as well as care quality and patient satisfaction even after accounting for the effect of EMR stages, and (3) the performance impact of EMRs are greater for hospitals with a lower degree of focus.

Keywords: Electronic medical records, hospital performance, focus

Introduction

In an attempt to improve care delivery, hospitals have invested in a broad array of information technology (IT) applications. It is believed that healthcare IT holds great potential to improve efficiency and care quality through secure use and sharing of patient health information. In particular, electronic medical record (EMR) can automate the capturing, storing, and sharing of patient records and are therefore crucial to the digitization and transformation of care delivery. Despite the anecdotal clinical benefits and cost savings, there is still a lack of empirical evidence on the long-term benefits of EMRs. A review of the relevant literature suggests that existing studies on EMR performance impacts has not considered the performance impact of post EMR-adoption experience or hospitals' operating characteristics in studying healthcare IT. In addition, prior studies treat EMR adoption as a one-time event whereas hospitals typically progress through various EMR stages, calling for analysis based on multi-year data tracking hospitals' progression through various EMR stages.

We propose to address the above limitations by performing a longitudinal analysis on a nationwide sample of U.S. hospitals. Our study contributes to healthcare operations management research by (1) providing a conceptual and operational differentiation between EMR stages and the experience associated with each EMR stage (*EMR experience* hereafter) as two aspects of EMR capabilities and empirically testing their respective performance impacts, (2) articulating and testing the differential performance impacts of lower and higher EMR stages and associated EMR experience , and (3) employing the operations management concept of focused factory to examine the moderation effect of hospital focus on EMR performance impacts.

Theoretical Foundation and Hypothesis Development

The resource-based view (RBV) of the firm and its variants provide the main theoretical foundation for our study. The *RBV* claims that the primary goal of the firm is to achieve competitive advantages through the deployment of *valuable*, *rare*, *inimitable*, and *non-substitutable* resources and capabilities (Barney 1991). Firms develop a competitive advantage when they are more effective than their rivals in picking, assembling, and deploying their assets to the productive use (Makadok 2001). Since EMR applications are readily available from multiple vendors on the market, purchase of EMRs does not differentiate a hospital from others that also have access to the same or similar EMR applications. As a hospital adopts a growing array of EMR applications and integrates these individual IT components into the care delivery process, the hospital increases its capability to "capture, store, retrieve, share, monitor, and analyze electronic medical information in a timely manner from disparate sources in the delivery of care" (Dey et al. 2012, p. 5). Thus, EMR infrastructure that integrates multiple related IT applications to facilitate coordinated care delivery through heterogeneous operational processes can be viewed as a capability.

According to EMR adoption model (EMRAM) by HIMSS Analytics, the sophisication of EMR systems ranges from the initial clinical data repository environment to a sophistcated EMR environment where paper documentation is no longer used. Lower stages of EMRs mainly include process-oriented EMR modules such as anicillary systems aiming at automating the capturing, retriving, sharing and exchanging patient information through a centralized clinical data repository.The process-based EMR modules can have direct impact on hospital operational performance by reducing record-keeping time and improving staff productivity (Kazley and Ozcan 2009, McAfee 2002). As hospitals reach higher EMR stages, appropriate documentations and inputs from nurses and physicians provide the ground for evidence-based clinical decision-support. The improved decision-making enabled by advanced EMR stages can have a significant impact on clinical outcomes and patient satisfaction (Queenan et al. 2011).

The expanded performance impacts from lower EMR stages to higher EMR stages are consistent with the literature that differenciates between exploration and exploitation aspects of IT (Kane and Alavi 2007). Organizations exploit knowledge regarding internal resources and processes to harness capabilities, reduce variability, and secure efficieny benefits. At the lower stages of EMRs, hospitals focus on using anicillary IT systems to automate the capture of patient information. These types of IT use reduces process variablity associated with patient heterogeneity and improves efficiency through sharing patient records with multiple stakeholders. In contrast, exploration leads to new knowledge that is radically different from existing body of knowledge (Gupta et al. 2006). At the higher stages of EMR, hospitals capitalize on the information repositories and use decision support functions to support evidence-based clinical decision making. By integrating context-specific rule-based clinical decision support messages, EMRs can also replace traiditional authority-based medicine with evidence-based medicine to enhance patient safety and generate cost savings (Rodwin 2001). These types of IT use can improved quality of decision making and help hospitals to treat patients more effectively, leading to enhanced clinical quality and satisfied patients (McAfee 2002). Thus, we propose the following hypotheses:

H1: The performance impact of EMRs varies across stages.

H1a: Hospitals at lower EMR stages will mainly achieve improvements in operational performance.

H1b: Hospitals at higher EMR stages will achieve improvements not only in operational performance, but also in care quality and patient satisfaction.

Another aspect of EMR capabilities rest on the experience accumulated through using EMRs to deliver care to patients. Literature suggests that IT-enabled capabilities such as EMRs' develop over the long-term through accumulation of experience and learning (Bharadwaj 2000). EMR capabilities build upon not only codified knowledge such as complex workflows and processes embedded in EMR systems, but also tacit knowledge residing in many individual users and their intertwined working relationships. As such, EMR capabilities are manifested not only in EMR sophistication, but also in the effectiveness of using EMRs to coordinate activities and delivery care. Such capabilities rely on tacit knowledge of EMR users at multiple levels and are rooted in actions rather than assets. The "contextually embedded nature" of knowledge and experience accumulated through technology use in organizations has been recognized in the literature (Edmondson et al. 2003). "Time compression diseconomies" (i.e., it takes time to accumulate resources) suggests that it is difficult to replicate or develop similar EMR capabilities within a short period of time (Dierickx and Cool 1989). Thus, strategic advantages built upon EMR experiences are likely to be sustainable. For similar reasons discussed earlier, we suggest that EMR experience with higher EMR stages will have positive effects on more aspects of hospital performance.

H2: EMR experience will have positive impacts on hospital performance.

H2a: The experience associated with lower EMR stages will mainly improve hospital operational performance.

H2b: The experience associated with higher EMR stages will improve not only hospital operational performance, but also care quality and customer satisfaction.

Hospitals epitomize the definition of "complex service organizations" (Tucker et al. 2007). Modern hospitals consist of multiple interdependent departments that frequently have conflicting goals and priorities but must coordinate their goals and priorities to deliver care. Thus, it is a major challenge to cope with the complexity of hospital operations. Literature has cited structural arrangements and information systems as viable means to deal with the information processing challenges that typically increases as organizations become more complex **(**Daft and Lengel 1986**).** Using information technology that enables task automation, virtual collaboration and decision-making provides an effective means to process large amounts of structured information. In the context of hospitals, EMRs enable the capture and retrieval of patient information from ancillary systems, provide decision support such as evaluating alternative treatments in the delivery of care, and enhance the treatment and prescription process by increasing compliance to clinical standards, thereby reducing medication errors due to illegible medication orders and improving clinical administration. However, these beneficial effects are likely to be higher in hospitals with lower levels of focus for two main reasons.

First, highly focused hospitals tend to specialize in one or several clinical areas and therefore their patients and operational procedures tend to be more homogenous than their counterparts. Literature drawing on organizational information processing theory suggests that increasing the focus of a firm should lead to reduced complexity of the firm and consequently a smaller amount of information that needs to be processed (Bozarth and Edwards 1997). The reduced amount of information processing implies that the need to implement information systems to automate information processing tasks will be lower, and if such systems are already in place, their impacts on performance are likely to be smaller. Second, focused hospitals are more likely to resort to non-technology mediated means to process information. In the manufacturing settings, focused factories are "characterized, among other things, by cross-functional teams, and superb communication…" (Ketokivi and Jokinen 2006). Similar to their manufacturing counterparts, due to the nature of focused hospitals, it is more likely for these hospitals to "abandon the traditional, functional, discipline-focused departments and in favor of a cross-functional design organized around patients and their diagnoses" **(**Hyer et al. 2009**)**. In such environments, it is easier for hospital staff and nurses to process information through interpersonal communication, leading to fewer needs for computer information systems.

In short, high focus not only reduces the criticality of using EMRs to process large amounts of information but provide a more conducive environment for alternative means of information processing. Thus, the impacts of EMRs in high focus hospitals are likely to be lower.

H3: EMR capabilities will have smaller impacts on hospital performance for hospitals with a higher level of focus.

H3a: EMR stages will have smaller impacts on hospital performance for hospitals with a higher level of focus.

H3b: EMR experience will have smaller impacts on hospital performance for hospitals with a higher level of focus.

Research Sample

The sample used in this study is a longitudinal data set that we compiled by combining four national databases related to hospitals' technology applications (Health Information Management Society, HIMSS), performance (Agency for Healthcare Research and Quality, AHRQ), costs (Centers for Medicare and Medicaid, CMS) and demographics (American Hospital Associations, AHA). We derived our study sample by matching hospitals that reported their IT application status in HIMSS database to those listed in the other three databases (i.e., we eliminated the hospitals that did not report EMR status). We were able to obtain 12,540 hospital-year observations involving 1,257 hospitals from 2000 to 2009.

EMR stages (EMRSTAGE) and EMR experience (EMREXP)

We captured EMR capabilities with respect to EMR stages and EMR experience and derived both measurements based on the HIMSS EMR adoption model and relevant EMR studies (Angst et al. 2010, Furukawa et al. 2011). Specifically, we grouped six key EMR applications into three groups representing different EMR stages. Each stage consists of a combination of different applications reflecting the completeness and sophistication of EMR systems. Hospitals in stage one should have implemented information systems across three ancillary departments (i.e., pharmacy, laboratory, and radiology) and a functional Clinical Data Repository (CDR). Hospitals in stage two should have implemented all applications in stage 1 plus Nurse Documentation (DOC) and Electronic Medication Administration Records (EMAR). Hospitals in stage three should have implemented all applications in stage two plus Clinical Decision Support (CDS) and Computerized Physician Order Entry (CPOE). Each EMR stage is coded as dichotomous variable capturing whether a hospital has completely adopted the combination of applications in corresponding stage. For instance, we coded *EMRSTAGE1* as a "1" if a hospital has adopted all four components of stage one EMRs (i.e., information systems for pharmacy, laboratory, and radiology, and CDR) and "0" otherwise. To remain consistent with the literature, we assume that each EMR application remains in place once it is adopted (Angst et al. 2010).

We next constructed three EMR experience measurements (EMREXP) corresponding to the proposed EMR stages. For each EMR stage, we compute the cumulative patient discharge after a hospital's complete adoption of EMR applications belonging to that stage. For instance, *EMREXP1* reflects a hospital's cumulative patient discharges following the hospital's complete adoption of one EMR applications (e.g., *EMRSTAGE1* = 1). *EMREXPs* of a hospital therefore capture experiences and learning accumulated by the hospital after it has completed EMR adoption at different stages. Our conceptualization and operationalization of EMR experiences are consistent with the organizational learning literature, which typically uses cumulative volume of production to capture the experience and learning accumulated over time and hence the capabilities achieved (Huckman and Pisano 2006).

Hospital performance measures

We used widely accepted performance measures from the healthcare literature to measure hospital performance (Becker and Sloan 1985, Devaraj and Kohli 2000, Hussey et al. 2009, Ozcan et al. 1992). We measure operational performance of each hospital with three variables: *COST*, *OCCUPANCY*, and *PRODUCTIVITY*. Following the healthcare efficiency typology (Hussey et al. 2009), we measure *COST* of a hospital using the average operating cost per patient discharge. We define *OCCUPANCY* as the actual usage of licensed beds by dividing the total adjusted patient days of a hospital by its number of licensed beds. *PRODUCTIVITY* captures the productivity of each full time equivalent employee (*FTE*) and is constructed by dividing the total adjusted patient days of a hospital by its number of FTEs. The clinical performance is assessed with a hospital-wide mortality ratio (*MORTALITY*), which aggregates the mortality ratios at three major treatment categories: heart attack, congestive heart failure, and pneumonia. These categories account for a high proportion of patients treated in hospitals. We measure patient satisfaction (*SATISFACTION*) using data collected by AHRQ through the HCAHPS (Hospital Consumer Assessment of Healthcare Providers and Systems) survey.

Hospital focus

Following the focused factory and the manufacturing strategy literature, we measure hospital focus with the Herfindahl–Hirschman index (*HHI*) (Mukherjee et al. 2000). Specifically, hospital focus is measured by the sum of the squared share of hospital beds allocated to different departments. We calculate hospital level *HHI* index for hospital h in year t as follows:

$$HHI_{ht} = \sum_i \left(\frac{Bedsize\ in\ Department_{iht}}{Total\ number\ of\ \ Hospital\ Beds_{ht}}\right)^2$$

Control variables

To isolate the effects of EMRs on performance, we control for typical factors that have been shown to affect hospital performance, including hospital age, size, cumulative volume, and case mix index (Becker and Sloan 1985, Hussey et al. 2009, Ozcan et al. 1992). These variables are presented in Table 1.

Table 1: Variable Description

Type	Variables	Description	Source
Independent	*EMRSTAGE* (EMR stage)	EMR stage, coded as a "1" if a hospital has adopted the combination of EMR applications for corresponding stage and "0" otherwise	HIMSS CMS
	EMRCAP (EMR capabilities)	EMR capabilities, defined as the cumulative patient discharges after a complete adoption of EMR applications at different stages.	
Operational outcomes	*OCCUPANCY* (Occupancy)	Ratio between total patient days and the total number of licensed beds	CMS
	PRODUCTIVITY (Productivity)	Ratio between total patient days and the number of FTEs	
	COST (Costs)	Ratio between total operating expenses and the number of patient discharges	
Clinical outcomes	*MORTALITY* (Mortality)	The hospital-level mortality rate	AHRQ
Patient outcomes	*SATISFACTION* (Patient Satisfaction)	Patient satisfaction, defined as the percentage of high ratings (9-10) among all of the ratings	AHRQ
Control variables	*CASEMIX* (Casemix Index)	Case mix index, defined as the average diagnosis-related group weight for all of a hospital's patient volume	AHA CMS
	BED (Staffed beds)	Staffed bed size, defined as the total number of staffed beds	
	FTE (Full time equivalent)	Full time equivalent employees	
	AGE (Hospital age)	Hospital age	
	MEDICARE (Pct. of Medicare)	The percentage of patient admissions from Medicare	
	MEDICAID (Pct. of Medicaid)	The percentage of patient admissions from Medicaid	
	YEAR (Observation year)	Year dummies	
	EXPERIENCE	Experience, defined as the cumulative patient discharges from 2000 to the observed year.	

Estimation Methods

Fixed Effects Models

We test our hypotheses with fixed-effects (FE) models. FE models are capable of controlling for unobserved heterogeneity that correlates with independent variables and remains constant over time. In our study, it is possible that some sample hospitals may exhibit both greater EMR capabilities and better performance, and this unobserved heterogeneity of individual hospitals is controlled for by FE models.

We performed a series of statistical tests to ensure the appropriateness of the FE model. We first performed a Hausman test (Hausman 1978) to compare the FE model with the random effects (RE) model. The *p*-value of the Hausman test is significant ($p < .001$), suggesting that the FE model is more appropriate for our data than the RE model. Next, we checked for autocorrelation using Wooldridge test, which rejected the null hypothesis that there is no first-order autocorrelation in the data ($p < .001$) (Wooldridge 2002). As suggested by Greene (2008), unbalanced panel data may also be subjected to groupwise heteroskedasticity. We performed a modified Wald test (Baum et al., 2000) to check for the heteroskedasticity in the residuals of the FE model. The results suggest the presence of groupwise heteroskedasticity in our dataset ($p < .001$). Given these data considerations, we estimated our models with robust standard errors (Wooldridge 2002). Robust standard errors relax the OLS assumptions that errors are independent and identically distributed. Researchers generally consider robust standard errors more trustworthy when autocorrelation and heteroskedasticity are present.

We use the Stata module *xtreg* to estimate our FE models, as shown below:

$$
\begin{aligned}
Y_{it} = {} & \beta_0 + \beta_1 CASEMIX_{it} + \beta_2 BED_{it} + \beta_3 FTE_{it} + \beta_4 AGE_{it} \\
& + \beta_5 MEDICARE_{it} + \beta_6 MEDICAID_{it} + \beta_{7s} \sum_{1}^{s} STATE_{ist} + \beta_{8y} \sum_{1}^{y} YEAR_{iyt} \\
& + \beta_{9e} \sum_{1}^{e} EMRSTAGE_{iet} + \beta_{10e} \sum_{1}^{e} EMREXP_{iet} + \beta_{11} EXPERIENCE_{it} + u_i + \varepsilon_{it}
\end{aligned}
$$

In the above equation, $i = 1,2, \ldots, N$, represents the i[th] hospital. $t = 1,2, \ldots, T$, represents the year. The variable u_i represents the hospital-level fixed effect. ε_{ij} is the random error term. We log transformed the performance variables to correct for skewness. We also included dummy variables for each calendar year to control for possible trend effects.

We first ran the FE models using the full sample to test the impact of EMR stages and EMR experience across all sample hospitals (models 1a through 5a in Table 2). To test the moderation effect of hospital focus, we median split sample hospitals by the hospital focus score. We then re-ran the FE models by the high focus hospital group (models 1b through 5b in Table 4) and the low focus hospital group (models 1c through 5c in Table 2) respectively. This method for testing moderation effects is based on the recommendation of Venkatraman (1989). Testing moderation effects by subgroup analysis is consistent with our moderation hypothesis specification and has been widely used by researchers to study impacts of technology across different levels of environmental characteristics (Eisenhardt and Zbaracki 1992). To test the robustness of our results, we also ran the FE models by splitting the sample into three and four subgroups. The results are consistent with those based on median split although somewhat weaker due to smaller sample size of each subgroup. The results presented in Table 2 are based on two subgroups created by median-splitting the sample hospitals. As an additional robustness check, we re-estimate the model with the full sample and the interaction effect between hospital focus and EMR capabilities. The results are largely consistent with the subgroup analysis. The coefficients of the interaction effect overall are somewhat weaker than the subgroup analysis, likely because the variation of focus within each hospital over time is not sufficient.

Table 2: Fixed-effects Model Results

	Cost per Discharge			Productivity			Occupancy			Mortality			Satisfaction		
	Full Sample (1a)	High Focus (1b)	Low Focus (1c)	Full Sample (2a)	High Focus (2b)	Low Focus (2c)	Full Sample (3a)	High Focus (3b)	Low Focus (3c)	Full Sample (4a)	High Focus (4b)	Low Focus (4c)	Full Sample (5a)	High Focus (5b)	Low Focus (5c)
Intercept	9.72***	9.46***	9.91***	1.86***	2.34***	1.44***	1.21***	1.34***	1.13***	2.81***	1.98**	3.17**	3.94***	4.11***	3.82***
Control variables															
CASEMIX	.074*	.063	.088^{*8}	.021	.051*	-.001	.032**	.033*	.029†	-.250	.120	-.454	.044	.022	.054
BED	-.086***	-.048†	-109***	.161***	.137***	.163***	-.205***	-.247***	-.175***	.027	.094	-.002	.009	-.015	.026
FTE	.028***	.031*	.028**	-.382***	-.452***	-.314***	.037***	.035**	.037**	-.002	-.002	-.006	-.004	-.001	-.008
AGE	-.017†	-.031*	-.005	.001	-.009	.013*	.013**	.016*	.012*	.082**	.007	.154†	.044†	.044†	.045
MEDICARE	.220***	.245**	.217**	-.057†	-.013	-.083*	-.049	.007	-.103*	-.541***	-.112	-.907***	-.061	-.154*	.032
MEDICAID	.126*	.136†	.128*	.074**	.057†	.065*	.040†	.006	.059*	-.042	.067	-.164	.015	.023	.013
YEAR	Included														
Independent variables															
EMRSTAGE1	-.004	.002	-.009	.005†	.007†	.007*	.006**	.004	.007**	.067***	.035**	.093***	.005	.009	-.001
EMRSTAGE3	-.002	.006	-.005	.013**	.015**	.011*	.005†	.006	.003	-.051**	-.015	-.074**	.023***	.023**	.021**
EMREXP1	-.023***	-.016**	-.030***	.008**	.014***	.005†	.011***	.011***	.011***	.005	-.018	.011	-.009	-.014	-.002
EMREXP3	-.011	-.013	-.008	.010*	.015*	.006	.003	.004	.001	-.069**	-.031	-.091**	.021**	.016	.026**
EXPERIENCE	-.001	-.001	.001	-.001	-.001	.001	-.000	-.001	-.002	.002	.001	.003	.002**	.003**	.001
F	41.29***	25.70***	19.27***	3.53**	3.29**	2.05**	22.86***	12.98***	13.48***	2.29**	1.70*	1.58**	24.83***	14.88***	12.31***
R^2	.233	.275	.201	.639	.725	.562	.291	.352	.255	.058	.025	.094	.201	.219	.197

† $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$

Results

Table 2 reports the regression results for the FE models. We initially included all three EMR stages in the model. Because a large number of hospitals adopted the EMR components that allowed them to reach stage two and stage three EMRs at the same time, the variable *EMRSTAGE2* and *EMRSTAGE3* exhibit extremely high correlation (r>0.85), making it impossible to empirically differentiate the two stages. Thus, we dropped the variable *EMRSTAGE2* from the analysis, allowing us to contrast the performance effects of *EMRSTAGE1* and *EMRSTAGE3*. In the analysis based on the full sample (models 1a through 5a), the *EMRSTAGE1* exhibits significant positive impacts on operational performance, including productivity (p<.10) and occupancy (p<.01). Interestingly, *EMRSTAGE1* is associated with higher mortality rate (p<.001), suggesting that earlier stages of EMR does not help improve care quality. In comparison, *EMRSTAGE3* not only positively affect operational performance such as productivity (p<.01) and occupancy ((p<.10), but also leads to significantly lower mortality rate (p<.01) and higher patient satisfaction (p<.01). These results suggest that lower EMR stages initially improves hospital efficiency and productivity, and over the longer-term, as hospitals reach higher EMR stages, clinical and patient outcomes start to improve. Thus, we find strong empirical support for *Hypothesis* 1.

We next examine whether EMR experience will have positive impacts on hospital performance. In the full sample (models 1a through 5a), *EMREXP1* exhibits significant impacts on each operational performance measure, including lower cost (p<.001), higher productivity (p<.01) and higher occupancy (p<.001). In comparison, *EMREXP3* not only positively impacts operational performance, but also leads to reduced mortality rate (p<.01) and improved patient satisfaction (p<.01). These results suggest that experience with lower stage of EMRs initially improves hospital operational performance, over the longer-term, experience with higher stages of EMR result in improvements in clinical and patient outcomes. These results support *Hypothesis* 2.

Finally, we examined whether EMR capabilities have less impacts on performance for more focused hospitals (i.e., *Hypothesis* 3).We found that, compared with high focused hospitals, EMR stages and EMR experience have significant effects on four of the five performance measures (*cost per patient discharge, occupancy, mortality and satisfaction*) in the expected direction for the low focus hospital subgroup. These results support *Hypothesis* 3.

Contributions

Our study makes three main contributions to the literature. First, drawing on the resource-based view, we differentiate between EMR stages and EMR experience. We further articulate and empirically examine the differing effects of EMR stages and EMR experience on various aspects of hospital performance. These are important extensions to the existing literature on EMRs. Our study provides both theoretical elaboration and empirical evidence demonstrating that EMR experience is important for uncovering the performance effects of EMRs. Second, our study appears to be the first to examine the long-term impacts of EMRs on a variety of hospital performance measures across hospital groups with different levels of focus. Prior studies on EMR performance have reported mixed results likely because these studies mainly use cross-sectional data and/or only examine a single aspect of hospital performance. To fill this gap in the literature, we assembled a multi-year dataset by consolidating four large-scale databases from multiple national healthcare agencies. Our empirical methods represent a considerable improvement over existing studies and therefore should generate more trustworthy and reliable results. Third, our study articulates a theoretical perspective based on organizational information processing theory and provides empirical evidence that the performance impacts of EMRs are context-dependent and hospital focus acts an important contextual factor that moderates the EMR- performance relationship. Our analysis indicates that high focus hospitals tend to benefit less from EMRs than their counterparts.

Discussion of results

Overall, our research findings help address several questions that have not been clearly answered in the literature. First, we show that hospitals persistent on developing EMR capabilities can expect to improve on a growing spectrum of performance dimensions over time, initially on operational performance and later on clinical quality and patient satisfaction. These results highlight that hospitals should establish a long-term plan to enhance both operational and clinical performance through a continuous cultivation of EMR capabilities rather than expect short-term returns from EMR investments. Second, our finding alleviates concerns that EMRs may lead to improvements on some aspects of performance (e.g., clinical performance and healthcare quality) while hampering performance in other areas (e.g., operational performance). In other words, we did not observe tradeoff with respect to the performance effects of EMR stages or EMR experience. Third, our results point to experience associated with EMR stages as an important theoretical construct for studying the performance impact of EMRs. As hospitals set forth to integrate additional functionalities into existing EMR systems, they need to make sure that hospital staff and nurses have opportunities to practice with newly added functionalities and become effective users. These findings corroborate the literature suggesting that hospital management should incorporate EMR functionalities to codify hospital routines and to create tacit knowledge in the form of know-how and know-what (Queenan et al. 2011, Tucker et al. 2007). Finally, our results indicate that the benefits of EMRs are context-dependent. It implies that omitting critical context factors may be an important reason that past research on EMRs has reported mixed results. This is an important finding because it suggests that a contingency perspective is promising for uncovering the potential performance impacts of EMRs.

Managerial implications

Our findings suggest that hospital administrators should evaluate EMRs in light of longitudinal hospital performance. If hospitals are committed to developing capabilities around EMRs and are persistent in doing so over the long term, investments in EMRs should pay off, leading to improvements along different aspects of hospital performance. Our finding that the performance impacts of EMRs are contingent upon hospital focus has useful managerial implications. When evaluating potential returns on EMRs, the degree of operating complexity as reflected by hospital focus and other relevant indicators should be taken into consideration. While focused operations may lead to improved hospital performance, not all hospitals are in a position to develop highly focused operations because of the nature of the hospitals. It may be unrealistic for some hospitals to choose the focus strategy because they may have to distribute resources across a variety of hospital services to meet healthcare needs from the communities they serve. Our results suggest that cultivating EMR capabilities may be especially important for hospitals that are not in a position to improve performance by increasing its degree of focus.

Limitations and future research directions

Notwithstanding the implications mentioned above, there are several limitations to our study. After dropping hospitals that did not meet selection criteria, our final sample presents only one third of the U.S. hospital population. Future studies should explore ways to obtain technology application status from the remaining two thirds of hospitals, which would more accurately capture the impact of EMRs on the entire hospital industry. We were unable to obtain additional observational data on the degree and frequency associated with the use of EMR technologies among hospitals in our sample. As an attempt to address this issue, we move beyond the dichotomous measure of EMR adoption by measuring EMR stages and experience associated with each stage. Future research should explore other options to collect actual EMR usage information (e.g., conduct observational studies or survey studies).

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