HEALTH INFORMATION TECHNOLOGY IN US HOSPITALS: ANALYSIS OF CURRENT STATUS AND DEVELOPMENT OF FUTURE STRATEGIES

A Dissertation

by

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ABSTRACT

Adopting Electronic Health Records (EHR) improves the efficiency and quality of health care systems. However, recent studies reported a slow rate of adoption or conflicting study results regarding EHR implementation in the United States. Even though there appears to be a substantial difference in terms of EHRs implementation and adoption among hospitals with different organizational characteristics and by end-users in different job categories, little has been studied about the relationship between EHR implementation and different organizational and end-users' characteristics.

To evaluate the current status of EHRs implementation and adoption and to compare how differences in organizational and end-user characteristics relate to EHR adoption and implementation, we analyzed secondary data from HIMSS Analytics® annual survey of 2013 and primary data from end-user surveys using various statistical analysis techniques including multivariable regression analysis, multinomial logistic regression analysis, and information theoretic analysis using normalized mutual information (NMI). This study was based on various theories including an organizational learning theory, a theory of organizational readiness for change, the Technology Acceptance Model (TAM) and Andersen and Aday's behavioral model.

We found discernable differences in EHR implementation and adoption among hospitals with different organizational contextual factors. Most notable was a strong link between hospital location and EHR implementation. Rural hospitals lagged behind urban hospitals in terms of EHRs implementation demonstrating a lower level of readiness for

meaningful use attainment. Hospitals in different locations selected and used different EHR vendors based upon location specific evidence related to attaining meaningful use. We also found that EHR end-users across different job categories had different perceptions toward EHRs, which ultimately influenced their satisfaction with EHRs.

For successful EHR implementation and adoption, health care managers need to develop and customize EHR implementation strategies. Instead of applying one uniform strategy, health care managers need to prioritize their resources and focus their efforts according to different organizational contexts and different end-user expectations toward EHRs. As rural areas will be disadvantaged in terms of quality and efficiency if rural hospitals continue to struggle with EHR implementation, we need to pay special attention to EHRs implementation in rural hospitals.

DEDICATION

To Him

SDG

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CHAPTER I

INTRODUCTION

Electronic health record (EHR) systems are believed to significantly improve the efficiency of health care systems and enhance the quality of care provided to patients (Wu et al., 2006). For this reason, the United States has developed major initiatives for the implementation of EHR systems. The Health Information Technology for Economic and Clinical Health (HITECH) Act, passed as part of the American Recovery and Reinvestment Act of 2009 (ARRA), established incentives for the meaningful use of EHRs, and thereby encouraging many health care providers to adopt EHR systems (Blumenthal, 2010). However, studies have reported a slow rate of EHR adoption due to several practical barriers (Boonstra & Broekhuis, 2010; Jha et al., 2009). Failure to implement or adopt EHRs not only incurs substantial costs to hospitals but may also hinder them from improving efficiency and overall quality of care (Bardhan & Thouin, 2012; Menachemi, Ford, Beitsch, & Brooks, 2007; Wu et al., 2006). Often-cited barriers to EHRs implementation include a lack of organizational support and end-users' resistance or their inability to use of EHRs (Bhattacherjee & Hikmet, 2007; Boonstra & Broekhuis, 2010; Hostgaard & Nohr, 2004; Jha et al., 2009; Tang, Ash, Bates, Overhage, & Sands, 2006). Currently, organizational support in implementation, such as resource allocation and the high-quality of end-user training, and leadership involvement throughout EHR implementation are known to facilitate EHRs implementation (Ash & Bates, 2005; Ash, Fournier, Stavri, & Dykstra, 2003).

There appears to be a substantial difference between rural and urban hospitals in terms of implementation and adoption of EHRs (Bahensky, Jaana, & Ward, 2008; Culler et al., 2006). Such a difference may potentially aggravate the disparity in the efficiency of health care systems and the quality of care across regions, but unfortunately, little is known about how EHR learning process differs between rural hospitals and urban hospitals. In addition to the more common barriers to EHR implementation, mismatch between EHR software and organizational practice goals can adversely affect the implementation of EHR systems (Bates, 2005; Boonstra & Broekhuis, 2010; Keshavjee et al., 2006). Despite the importance of EHR vendor selection, few studies about strategies for EHR vendor selection have been published and little is known about the relationship between EHR vendor selection and organizational learning processes that may be affected by hospital location (D. W. Bates, M. Ebell, E. Gotlieb, J. Zapp, & H. C. Mullins, 2003; McDowell, Wahl, & Michelson, 2003). As EHRs support the work of end-users with varying job tasks in different ways, and the degree to which EHRs serve those job responsibilities may affect end-users' expectation regarding EHRs, satisfaction with EHRs and acceptance of EHRs. However, few studies have examined the relationship between end-users' differing roles depending on their job categories and their expectations or satisfaction regarding EHRs (Dansky, Gamm, Vasey, & Barsukiewicz, 1998; Gamm, Barsukiewicz, Dansky, & Vasey, 1998).

Designing implementation and adoption strategies according to organizational characteristics and end-users' expectations is important to a successful EHR implementation because current known barriers and success factors may work differently depending on the details of organizational and end-users' contexts. Therefore, in this research, we aimed to evaluate the current status of EHRs implementation and adoption in U.S. hospitals and health care organizations and systematically compare how differences in locational, organizational, and end-users' characteristics of health care organizations relate to such adoption and implementation. Towards this goal, we analyzed secondary data consisting of the 2013 annual survey of the Healthcare Information and Management Systems Society (HIMSS) Analytics® database, as well as primary data collected from end-user surveys of an integrated health care system in Texas.

To develop the theoretical frameworks of this research, we used elements of an organizational learning theory (Levitt & March, 1988), a theory of organizational readiness for change (Weiner, 2009), the Technology Acceptance Model (TAM) (Davis, 1989), and Andersen and Aday's behavioral model (Andersen, 1995).

Various statistical analysis techniques, including multivariable regression analysis, multinomial logistic regression analysis, and information theoretic analysis using normalized mutual information (NMI), were used to analyze the data and test the proposed hypotheses. Especially, this research introduced a new method, NMI, rooted in information theory and widely used in electrical engineering and the computer science field to health service research. This research has a strong potential for developing effective strategies for successful EHRs implementation and adoption according to different organizational contexts within the United States.

The following chapters cover the three topics stemming from this research.

1. Assessment of the differences in the levels of organizational readiness to attain meaningful use of EHRs associated with hospital location (rural and urban) as well as other organizational factors that related to the readiness to attain meaningful use of EHRs.
2. Assessment of the relationship between EHR vendor selection and organizational contextual factors such as hospital locations, organizational practice goals, and financial resources.
3. Assessment of end-users' perception toward EHRs' contribution to their job activities across different job categories (provider, other clinical and non-clinical), the relationship between those perceptions toward EHR implementation and their satisfaction with EHRs across different health care job categories.

CHAPTER II

HOSPITAL CHARACTERISTICS ARE ASSOCIATED WITH READINESS TO ATTAIN STAGE 2 MEANINGFUL USE OF ELECTRONIC HEALTH RECORDS

Background and Significance

It is widely believed that adopting electronic health record (EHR) systems will significantly improve the efficiency of health care systems and enhance the quality of care provided to patients (D. W. Bates, M. Ebell, E. Gotlieb, J. Zapp, & H. Mullins, 2003; Wu et al., 2006). For this reason, the United States has developed and funded major initiatives for the implementation of EHR systems. Specifically, the Health Information Technology for Economic and Clinical Health (HITECH) Act, passed as part of American Recovery and Reinvestment Act of 2009 (ARRA), established a framework for incentive payments for meaningful use of EHRs and since 2009 has encouraged many healthcare providers to adopt EHR systems (Blumenthal, 2010; The Centers for Medicaid and Medicaid Services, 2014).

Meaningful use is defined as providers' "use of EHR in ways that positively affects patient care (The Centers for Medicare and Medicaid Services, 2014)." To receive incentive payments for meaningful use of EHRs, as defined by the Centers for Medicare and Medicaid (CMS), eligible health care organizations need to meet requirements pertaining to three stages of EHR adoption. According to the CMS, the three stages for meaningful use should be met sequentially over five years. For Stage 1, the requirements are focused on data capture and sharing. The focus shifts to advanced clinical processes for Stage 2, and to improved outcomes for Stage 3. Hospitals can qualify for an incentive payment for Stage 1 by attesting to have met Stage 1 requirements based on attaining at least 18 of 23 meaningful use objectives. Hospitals must meet Stage 2 objectives in addition to Stage 1 objectives in order to receive an incentive payment for Stage 2 (The Centers for Medicaid and Medicaid Services, 2014).

Success in fulfilling requirements for meaningful use will be the critical criterion in health care reform's drive for improved quality and efficiency in the healthcare system (Jha, 2010). Attaining meaningful use of EHR systems will help healthcare providers avoid prescription errors and improve the quality of medical record-keeping. As well, it will enhance access to medical records for both providers and patients. Meaningful use will facilitate these improvements by ensuring that providers and other allied health professionals have better access to accurate clinical information not only within their individual hospital system, but across multiple hospital systems that communicate with each other by exchanging clinical data.

Even though a growing number of hospitals have implemented EHR systems in recent years, studies have shown that many hospitals have struggled to do so because of practical barriers (Boonstra & Broekhuis, 2010; Jha, 2010; Jha et al., 2009). Overall, the rate of EHR adoption has been slower than expected. Some studies reported that hospitals in small towns and rural areas have especially lagged behind in EHR adoption (Adler-Milstein, DesRoches, et al., 2014; Bahensky et al., 2008; Culler et al., 2006; DesRoches, Worzala, Joshi, Kralovec, & Jha, 2012). As a result, concerns have emerged about the future of rural hospitals—the fear that slow adoption may leave rural areas disadvantaged in terms of both the quality and the efficiency of health care delivery. A lower level of EHR adoption in some areas may also hinder the interoperability of EHRs across the nation (Goldschmidt, 2005). However, several national studies using different data reported conflicting results about the rate and level of EHR adoption. Some studies have found no difference in the level of EHR adoption between rural and urban hospitals (DesRoches et al., 2008; Hing, Burt, Woodwell, & Statistics, 2007; Singh, Lichter, Danzo, Taylor, & Rosenthal, 2011). Given the currently available conflicting results about the level of EHR adoption in different locations, it seems advisable—before debating next steps—to first take a closer look at the present status of EHR adoption across rural and urban hospitals in the United States. The purpose of this study is to ascertain whether, any meaningful differences in EHR adoption exist between rural and urban hospitals in the United States.

EHR implementation should be viewed as a major dynamic organizational learning process as EHR is a new knowledge and a routine change to end-users (Crossan, Lane, & White, 1999). There have been many studies about the critical factors for successful EHR implementation and adoption by health care organizations. Current known facilitators of implementation are communication with end-users, leadership involvement, and training (Ash & Bates, 2005). Current known barriers are lack of organizational support, such as financial and staff resources, and end-users' resistance to change (Boonstra & Broekhuis, 2010; Tang et al., 2006). However, these factors affect hospitals differently depending on the details of their organizational contexts. According to Weiner, organizational contextual factors invariably affect the effectiveness of organizational change (Weiner, 2009). In other words, commonly known success factors identified in the literature may work differently in different contexts. Hospital locations (rural or urban) and other organizational contextual factors such as its organizational culture, policies and procedures, past experience, organizational resources, and organizational structure are all possible factors that impact the effectiveness of EHR adoption (Weiner, 2009).

This study aimed to examine the difference between rural and urban hospitals with regard to their overall level of organizational readiness for Stage 2 meaningful use of EHRs and to identify other key factors that affect hospitals' level of organizational readiness for attaining Stage 2. Using the model proposed in this paper (Figure 1), we tested our hypotheses 1) that rural hospitals are less likely than urban hospitals to be ready for Stage 2 meaningful use of EHRs and 2) that particular identifiable contextual factors differently affect these hospitals' level of organizational readiness for attaining Stage 2 meaningful use of EHRs.

Figure 1 Theoretical framework

Materials and Methods

Theoretical framework

Figure 1 illustrates the theoretical framework used in this study. It explains that hospital location affects the organizational contextual factors and these different organizational contextual factors affect the readiness for Stage 2 meaningful use of EHRs.

Data

The data used in this study were collected on 5,467 hospitals in the United States from the HIMSS Analytics® annual survey of 2013. The survey provided data on a variety of organizational characteristics as well as information pertaining to health information technology including the current status of EHRs adoption.

Sample

The sample for this study included 2,083 hospitals in the United States that participated in the HIMSS Analytics® annual survey of 2013 and answered the survey's questions regarding the attestation to CMS of meaningful use of EHRs.

Model building

The Stage 2 benchmark of meaningful use became effective in 2014. Hospitals must meet Stage 1 meaningful use criteria for two or three years to become eligible to receive the incentive payment for Stage 2 meaningful use. The attestation regarding attainment of Stage 1 meaningful use is the starting point of hospitals' readiness for Stage 2. Thus, the dependent variable in this study was a dichotomous variable indicating that attestation for having met Stage 1 meaningful use requirements has been provided, or not.

The primary independent variable in this study was hospital location (rural or urban). According to United States Census Bureau, Core Based Statistical Areas (CBSAs) refer to both of metropolitan and micropolitan statistical areas (U.S. Census Bureau, 2012). Hospital location was coded to "rural area" if the data field in the CBSAs database for information about hospital location was left blank. Otherwise, hospital location was coded to "urban area." Other covariates were categorized into five contextual factor constructs suggested by Weiner (Weiner, 2009). These other covariates were (1) the mandate of physicians' utilization of a Computerized Physician Order Entry

(CPOE) system for the construct of organizational culture; (2) organizational type (government, for profit, or not-for-profit) for the construct of organizational policies and procedures; (3) participation in an Information Exchange (IE) initiative for the construct of past experience; (4) the ratio of Information System (IS) Full Time Equivalent (FTE)s to total FTEs, IS FTEs that support EHR applications, IS FTEs at the helpdesk, and IS FTEs in management for the construct of organizational resources; and (5) the existence of a Chief Information Officer (CIO) position with responsibility for health information management for the construct of organizational structure.

Analysis

Descriptive statistics were used to examine differences in the current level of hospitals' readiness for Stage 2 meaningful use with reference to U.S states, U.S census regions (Northeast, Midwest, South, or West), organization type (government, for-profit, or non-profit), and ownership status (leased, owned, or managed).

Before conducting a multivariable logistic regression analysis, bivariate logistic regression analysis was first used to discern a possible relationship between hospitals' readiness for Stage 2 by location. Bivariate analysis was also performed to investigate the potential relationship between hospitals' readiness for Stage 2 and each organizational contextual factor.

Due to the high degree of multicolinearity among variables and different patterns of responses and missing response, five different regression models were built instead of a single model with all variables. These five models used the primary independent variable (hospital location) and different covariates from the five constructs derived from organizational contextual factors (organizational culture, organizational policies and procedures, past experience, organizational resources, and organizational structure). This approach was taken in order to test a non-nested alternative hypothesis in each of the five models and to select significant covariates based on the resulting p-values (Pesaran & Deaton, 1978). Multivariable logistic regression analysis was conducted with the final model including the main independent variable (hospital location) and significant covariates selected from the five aforementioned models to estimate the odds ratio (with a 95% confidence interval) for the independent effect of hospital location and organizational contextual factors on hospitals' readiness for Stage 2 meaningful use of EHRs.

Access to the HIMSS Analytics data was obtained from HIMSS Analytics by the Texas A&M Health Science Center School of Public Health. The study was reviewed and approved by the Texas A&M University Institutional Review Board (IRB).

Results

Descriptive statistics

As shown in Figure 2, hospitals in different states reported different levels of readiness for Stage 2 meaningful use of EHRs. Specifically, the sample proportion of hospitals reporting the attainment of Stage 1 meaningful use in the Northeast (92%) and in the South (87%) was greater than that for hospitals in the West (79%) or in the Midwest (86%) as shown in Table 1. Overall, the sample proportion of hospitals reporting the attainment of Stage 1 meaningful use was 86%, which was about same as that in Midwest (86%) and slightly lower than that in the South (87%) (Table 1). The sample proportion of rural hospitals reporting the attainment of Stage 1 meaningful use was 79%, which was lower than that of urban hospitals (88%) (Table1).

Figure 2 States' readiness for Stage 2 meaningful use of EHRs 2013

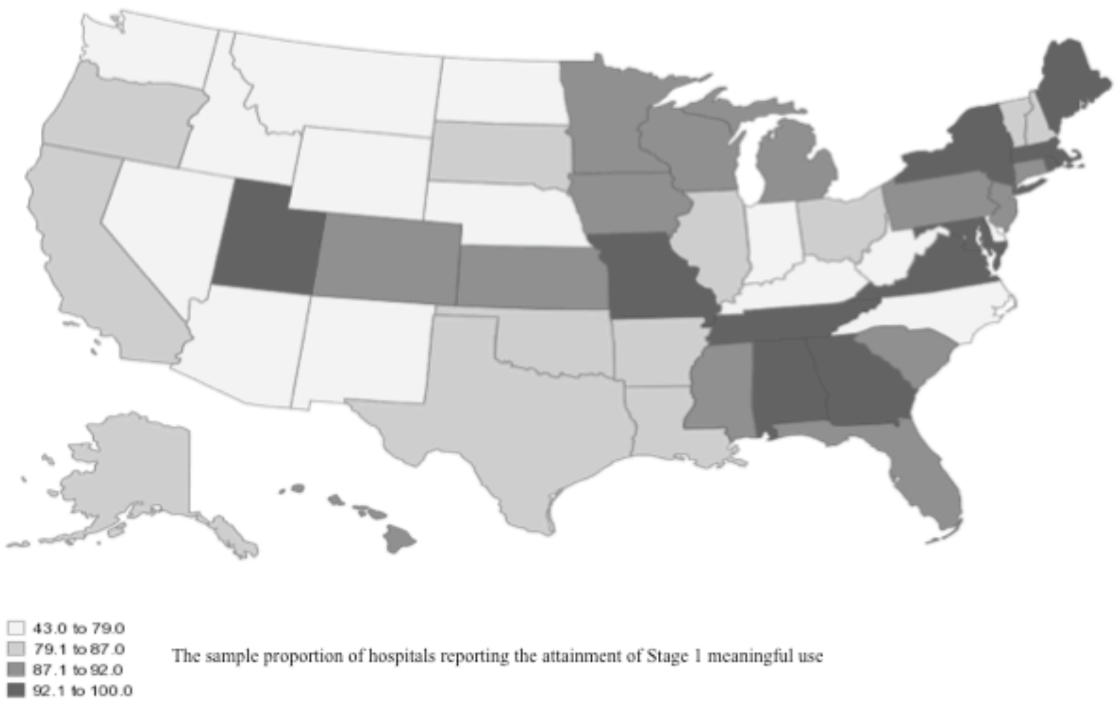


Table 1 Descriptive statistics

		N	Ready for Stage 2 Meaningful use (%)	Not Ready for Stage 2 Meaningful use (%)	P-value
Location	Total	2,083	86	14	P<0.001
	Rural	395	79	21	
	Urban	1,688	88	12	
Region	Total	2,083	86	14	P<0.001
	Northeast	296	92	8	
	Midwest	644	86	14	
	South	787	87	13	
	West	356	79	21	
Organization Type	Total	2,055	86	14	0.007
	Government	429	81	19	
	For-profit	250	88	12	
	Not-For-Profit	1376	87	13	
Ownership Status	Total	2,083	86	14	0.404
	Leased	31	90	10	
	Managed	69	81	19	
	Owned	1983	86	14	

The level of readiness for Stage 2 also varied with reference to the type of organization and ownership. Government hospitals were less likely to be ready for Stage 2 than were for-profit and not-for-profit hospitals (Table 1). The majority of hospitals in our sample were operated by their owners. However, the results showed that leased hospitals might have been more likely to be ready for Stage 2 than managed or owned hospitals, though the observed difference was not statistically significant (Table 1).

Regression results

We analyzed the effects of each 5 construct on hospitals' readiness for Stage 2 meaningful use after adjusting for hospital location as summarized in Table 2. As to organizational culture, hospitals that mandated CPOE were more likely to be ready for Stage 2 meaningful use than those who did not (OR=1.26, P=0.212). Table 2 also shows the effects of organizational policies and procedures on hospitals' readiness for Stage 2 meaningful use. Both of for-profit hospitals (OR=1.68, P=0.024) and not-for -profit hospitals (OR=1.54, P=0.0003) were more likely to be ready for Stage 2 meaningful use than government hospitals. Hospitals that had experienced IE in the past showed the higher level of readiness for Stage 2 meaningful use (OR=1.73, P<0.001) compared to those who did not have any past experience. As to the effect of organizational resources on the readiness for Stage 2 meaningful use, hospitals with more human resources related to IS management and EHR support were more likely to be ready for Stage 2 meaningful use. Different organizational structure also affected hospitals readiness for Stage 2. In case hospitals that made CIO in charge of health information management, they showed higher level of readiness for Stage 2 (OR=1.52, P=0.023) (Table 2).

Table 2 Estimates of effect of hospital location and other factors on the readiness for Stage 2 meaningful use of EHRs

Variable	Model Predicting Readiness for Stage 2 Meaningful Use							
	Not Adjusted				Adjusted Estimate			
	N	**Odds Ratio**	**(95% CI)**	**P-value**	**N**	**Odds Ratio**	**(95% CI)**	**P-value**
Rural	2083	0.55	(0.41-0.73)	<0.001	1414	0.61	(0.41-0.93)	0.020
CPOE mandated [*1]	1414	1.26	(0.88-1.80)	0.212	1414	1.17	(0.82-1.69)	0.386
Rural	2083	0.55	(0.41-0.73)	<0.001	2055	0.59	(0.43-0.79)	0.001
Org Type	2055				2055			
-Government		base	--	--		base	--	--
-For Profit		1.68	(1.07-2.64)	0.024		1.37	(0.86-2.19)	0.191
-Not for Profit		1.54	(1.15-2.06)	0.003		1.30	(0.96-1.77)	0.092
Rural	2083	0.55	(0.41-0.73)	<0.001	1806	0.59	(0.44-0.79)	<0.001
IE initiative [*2]	1806	1.73	(1.34-2.24)	<0.001	1806	1.63	(1.25-2.12)	<0.001
Rural	2083	0.55	(0.41-0.73)	<0.001	795	0.65	(0.42-1.01)	0.055
Ratio of IS FTEs to total FTEs	973	1.004	(1.0003-1.0070)	0.011	795	1.008	(1.002-1.013)	0.003
IS FTEs supporting EHR applications[*3]	833	1.51	(1.06-2.17)	0.024	795	1.55	(0.99-2.41)	0.054
IS FTEs at Helpdesk	831	1.47	(1.02-2.10)	0.037	795	1.48	(0.95-2.29)	0.080
IS FTEs in management	838	2.19	(1.20-3.98)	0.015	795	1.71	(0.68-4.28)	0.254
Rural	2083	0.55	(0.41-0.73)	<0.001	1305	0.50	(0.36-0.70)	<0.001
CIOHIM [*4]	1305	1.52	(1.05-2.20)	0.023	1305	1.48	(1.02-2.15)	0.041

*1 Did the healthcare system mandate that physicians utilize a CPOE system?
*2 Does the hospital participate in an Information Exchange Initiatives?
*3 Does the hospital have Information System (IS) FTEs that support EHR applications?
*4 Does the hospital Chief Information Officer (CIO) have responsibility for Health Information Management (HIM)?

Hospitals’ past experience with IE initiatives (OR=1.63, P<0.001), the existence of FTEs supporting EHR applications (OR=1.55 P=0.054), the ratio of IS FTEs to total FTEs (OR=1.008, P=0.003), and CIO’s responsibility for health information management (OR=1.48, P=0.041) were identified as the most critical organizational contextual factors that affect hospitals' readiness for Stage 2 meaningful use of EHRs after adjusting for hospital location (Table 2). The result of the final model including these statistically significant variables and hospital was summarized in Table 3. Rural hospitals were generally less likely to be ready for Stage 2 when compared to urban hospitals (OR=0.52, P=0.008) after adjusting for other critical factors including hospitals’ past experience with IE initiatives, human resources in IS departments, human resources in EHR support, and CIO’s responsibility for health information management.

Table 3 Estimates of effect of hospital location and other critical factors on the readiness for Stage 2 meaningful use of EHRs

Variable	Model Predicting Readiness for Stage 2							
	Not Adjusted				Adjusted Estimate			
	N	Odds Ratio	(95% CI)	P-value	N	Odds Ratio	(95% CI)	P-value
Rural	2083	0.55	(0.41-0.72)	<0.001	625	0.49	(0.30-0.89)	0.003
IE Initiative	1806	1.73	(1.34-2.24)	<0.001	625	1.89	(1.23-2.92)	0.004
Ratio of IS FTEs to total FTEs	973	1.004	(1.0003-1.0070)	0.031	625	1.006	(1.0007-1.0116)	0.027
FTEs supporting EHR applications*1	833	1.51	(1.06-2.17)	0.024	625	1.46	(0.89-2.38)	0.135
CIOHIM *2	1305	1.52	(1.05-2.20)	0.028	625	1.75	(0.96-3.16)	0.066

*1Does the hospital have Information System (IS) FTEs that support EHR applications?
*2 Does the hospital Chief Information Officer (CIO) have responsibility for Health Information Management (HIM)?

Discussion

The results of this study indicate a strong link between hospital location and readiness for Stage 2 meaningful use of EHRs by supporting our hypothesis 1) that rural hospitals are less likely than urban hospitals to be ready for Stage 2 meaningful use suggesting that many rural hospitals still lag behind in EHR adoption and still face the challenge of meeting Stage 1 meaningful use requirements. Meanwhile, Stage 2 meaningful use requirements have been in effect since January 2014. Because hospitals must meet Stage 1 meaningful use requirements in order to qualify for Stage 2 meaningful use incentive payments but many rural hospitals are still struggling to meet Stage 1 requirements, the incentive payments already in place for Stage 2 are eluding these facilities. This lower level of readiness for Stage 2 among rural hospitals will not only leave rural areas disadvantaged in terms of the quality and efficiency of available health care but will also hinder the interoperability of EHRs among providers across the nation. To achieve the national goal, an overall improvement of quality and efficiency in healthcare, we need to remove this substantial difference in the pace of EHR adoption between rural and urban hospitals.

This study's findings also supported our hypothesis 2) that particular identifiable contextual factors differently affect these hospitals' level of organizational readiness for attaining Stage 2 meaningful use of EHRs suggesting that rural hospitals may partially offset the disadvantages of rural status on their level of readiness for Stage 2 meaningful use of EHRs by allocating additional resources to their IS departments, and by installing a CIO with responsibility for taking charge of their health information systems. Our results did not indicate that IS support for the EHR applications was a statistically significant factor in this problem, even when the variable with a count of IS FTEs that support EHR applications was recoded to assume hospitals with missing values had no IS support (0 FTE). The identification of critical factors that were associated with the adoption of EHR provides insights into possible organizational change efforts that were likely to help rural hospitals succeed in meeting meaningful use requirements and thereby attaining the desired improvement of quality and efficiency in healthcare delivery (Weiner, 2009).

Many rural providers use up their resources when they purchase expensive EHR systems and fail to use their incentive payments to educate their staff and patients and customize their new EHR systems (Rudansky, 2013). A recent study found that rural and small hospitals showed more homogeneous and standardized EHR adoption patterns than urban hospitals (Adler-Milstein, Everson, & Lee, 2014). This scenario is likely to result in greater challenges—and delays—in meeting Stage 2 requirements, which are more focused on the active exchange of health information internally and externally among providers and patients. Due to the high initial cost of implementing EHR systems, it is likely to be very difficult if not impossible for many rural hospitals to meet requirements for Stage 2 meaningful use. Start-up funds are necessary for rural hospitals to invest in EHRs. Loan programs for rural and small hospitals may be necessary to help them meet Stage 2 requirements.

Our results suggest that rural hospitals might need to invest proportionately more resources in IS to overcome the barriers to meaningful use inherently associated with rural location such as a lack of Information Technology (IT) infrastructure and qualified IT professionals. The current lack of digital infrastructure in many rural areas will of course further burden rural providers as they strive to attain Stage 2. Due to the lower level of broadband communications infrastructure and internet connectivity coverage in rural areas as compared to urban areas, it is predictable that rural hospitals will continue to struggle to become hubs of efficient health communication (Alverson, 2004). Rural hospitals also face difficulties in staffing in all areas, not least in their IT departments. High turnover of staff and the lack of new and sustainable staff are a perennial challenge (AHA, 2007; AHRQ, 2009; Ward, Jaana, Bahensky, Vartak, & Wakefield, 2006). The reality is that staff in rural hospitals already tend to assume multiple tasks and are not readily able to assume additional IT tasks which often require much more effort and time. Consequently, experienced IT specialists are in high demand, and it is challenging for providers in rural areas to find enough local IT professionals to help them meet meaningful use criteria.

Another challenge facing rural hospitals to attain meaningful use is characteristic of rural populations that they serve. Rural residents tend to be older and less likely to have internet access, and those who do have internet access and good computer literacy may disproportionately commute to urban areas for both their work and health care services. This will make it even harder for rural hospitals to engage patients in communicating through EHR systems, one of the important goals of Stage 2 meaningful use. Educating patients may in time increase the level of EHR use in the way that CMS suggests. However, education efforts involve costs as well, which will be a further burden on rural hospitals.

Finally, rural patients are more likely than urban patients to have Medicare as their principal source of payment (Hall & Owings, 2014). From 2015 CMS will start imposing a penalty on providers who participate in Medicare but are not able to meet meaningful use requirements by 2015 (DesRoches, Worzala, & Bates, 2013). A reduction in Medicare payments will further aggravate the financial predicament of rural hospitals and will likely make it even more challenging for them to attain Stage 2.

This study has several limitations. First, the design of this study is cross-sectional. Even though we identified the relationship between hospitals' readiness for Stage 2 meaningful use and other critical contextual factors, this result may not provide cause-and-effect relationship. In addition, the sample size of our study was small. The response rate for the question regarding attestation for having met Stage 1 meaningful use was 38%. While we tried to minimize the proportion of missing data caused by different patterns of item non-responses across respondents by building up the final model only with statistically significant variables after estimating five different models according to 5 different constructs related to organizational readiness for change, the sample size in our final model for analysis was relatively small. This may lead to potential bias in determining the relationship between hospitals' readiness for Stage 2 meaningful use and critical factors identified in this study.

Conclusion

Rural hospitals have struggled more to attain meaningful use criteria and may eventually face penalty for not having attained meaningful use criteria. Regardless of other change related efforts identified in this study that hospitals may input to increase the level of readiness for Stage 2 meaningful use, rural hospitals are more likely to be left behind due to their limited resources.

To help rural hospitals increase their level of readiness for Stage 2 meaningful use and receive the incentive payments they badly need, modified and differentiated time schedules could be developed and proposed to rural hospitals. For those who haven't yet attained Stage 1 meaningful use, it may be time to consider the adoption of a different, more realistic timeline for attaining Stage 2.

In light of evidence of recent increases in the number of closures among rural hospitals, it is increasingly important that EHR strategies contribute to the ability of rural hospitals to attract patients now and again in the future(The Cecil G. Sheps Center for Health Services Research, 2014; Wilson, Kerr, Bastian, & Fulton, 2014). Increased attention might well be given to how an EHR can contribute the quality of patient care during and after a rural hospital visit and how it can link the hospital to physicians, labs, pharmacies and referral hospitals.

CHAPTER III

SELECTING A SUITABLE EHR VENDOR

Background and Significance

Electronic health record (EHR) systems have the potential to assist healthcare providers improve the quality and efficiency of their patient care efforts. However, to achieve the full benefit of the EHR, providers must overcome numerous barriers. As such, EHR implementation can be viewed as an organizational learning and change process. EHR vendor selection is one of the most important steps in the beginning process of EHR implementation. Beyond often cited barriers to an EHR implementation, such as the lack of resources and end users' resistance to change, a mismatch between EHR vendors' products capabilities and characteristics and hospitals' clinical work processes can have a significant adverse effect on the implementation of EHRs (Bates, 2005; Boonstra & Broekhuis, 2010).

The Centers for Medicare and Medicaid Services (CMS) has published a list of certified EHR vendors (The Centers for Medicaid and Medicaid Services, 2014). However, even with this list, it is hard to select the right vendor because so many certified EHR vendors available in the market are included in the list of CMS and each EHR vendor has a different spectrum of operating functions, capabilities, and operating expenses. To select a vendor that suits an organization among the many available vendors, hospitals need to consider organizational practice goals and learn from similar practices using the same vendor (HIMSS EHR Usability Task Force, 2010). Hospital location as well as other organizational contextual factors such as organizational practice goals and financial resources may affect vendor selection due to the different capable function and costs of EHR systems (Bassi & Lau, 2013; Wu et al., 2006). Selecting a suitable EHR vendor also affects whether meaningful use is attained. The first step to attain meaningful use is selecting a suitable and certified EHR system that is capable of meeting requirements published by CMS over different 3 stages (The Centers for Medicaid and Medicaid Services, 2014).

Despite the importance of EHR vendor selection, a few studies about strategies for EHR vendor selection have been published (D.W. Bates et al., 2003; Holbrook, Keshavjee, Troyan, Pray, & Ford, 2003; Lorenzi, Kouroubali, Detmer, & Bloomrosen, 2009; McDowell et al., 2003; Susan Rehm & Kraft, 2001). Furthermore, little is known about the relationship between vendor selection and organizational learning processes that are potentially affected by hospital location. Regardless of its crucial role in a successful implementation of EHR, little attention has been paid to the relationship between vendor selection and organizational contextual factors.

This study examines the current status of EHR vendor selection as well as relationships between hospital location and other organizational contextual factors, including type of hospitals, organizational practice goals, and financial resources, and EHR vendor selection. In this study, we tested the following hypotheses: 1) rural and urban hospitals select different EHR vendors, 2) organizational contextual factors are associated with EHR vendor selection, and 3) hospitals in similar locations (rural or urban) that selected similar EHR vendors are more likely to succeed in attaining Stage 1 meaningful use.

Materials and Methods

Data

The data for this study were collected on 5467 hospitals in the United States from the HIMSS Analytics® Database from 2013. The data included various aspects of organizational characteristics and information related to health information technology including names of EHR vendors that hospitals selected, the status of EHR implementation and the applications of EHR used.

Sample

The sample of this study consisted of 4511 hospitals in the United States that participated in HIMSS Analytics annual survey of 2013 and answered the questions regarding EHR vendors and applications that they implemented in their systems.

Model building

Hospitals were asked the name of the EHR software vendors utilized and the status of applications. Available responses for the status of applications were the following: contracted/not yet installed; installation in process; live and operational; not automated; not reported; not yet contracted; service not provided; to be replaced. The dependent variable in this study was EHR vendor, which was live at U.S hospitals. For our dependent variable, vendor selection was treated as categorical without any natural order, and it was coded to 5 categories (Meditech, CPSI, Epic, MedHost and "other"). This coding convention was developed because the number of different vendors selected was too numerous to include all as unique categories. We selected the specific vendors included as unique categories after listing vendors by market share according to hospital location (rural or urban). We included the vendors with the largest market shares among urban hospitals (MEDITECH) and among rural hospitals (CPSI). We also included Epic and MedHost as unique categories, because they were the only other vendors among the top 5 vendors in terms of market share for both urban and rural hospitals. All remaining vendors were coded to "other".

The primary independent variable in this study was hospital location (rural or urban). Hospital location was coded as rural area if the field Core Business Statistical Area (CBSA)(United States Census Bureau, 2012) where the entity was located was blank. Otherwise, hospital location was coded as urban area. Other covariates in this study were the type of hospitals (government, for-profit, or not-for–profit), organizational practice goal (participation in Information Exchange (IE) initiative) and financial resources (revenue per Full-Time Equivalent (FTE)). If hospitals either participated or had a plan to participate in information exchange, we indicated that they had practice goal of IE. We divided net patient revenue by the number of FTE to calculate net patient revenue per FTE. The unit of revenue per FTE was coded in $10K.

Analysis

We identified the number of EHR vendors used per hospital and examined how hospitals use EHR vendors for different EHR applications. We also examined differences in the current market share of EHRs by hospital location (rural or urban). A representative of each hospital was asked to identify which EHR vendor was used for each of seven applications. To examine the market share of EHRs, we included only live and operational EHR vendors and calculated the number of applications for which the same vendor was used at each hospital. After calculating the number of applications that the same EHR vendor used at each hospital, we included EHR vendors that were used for more than 3 out of 7 applications of EHR, given that about 60 percent of hospitals used the same EHR vendor for more than 3 applications. In other words, when hospitals used the same EHR vendors for more than 3 applications, we viewed those EHR vendors as the EHR vendors selected by the hospitals. The 7 EHR applications were clinical data repository, Clinical Decision Support System (CDSS), Computerized Practitioner Order Entry (CPOE), order entry (includes order communications), patient portal, physician documentation, and physician portal.

Bivariate multinomial logistic regression analysis was conducted to see what relationship exists between the selected EHR vendors and hospital location (rural or urban), organizational type (government, for-profit, or not-for-profit), hospitals' practice goal (IE initiative) and the revenue per FTE. The referent group of vendor was other. Multinomial logistic regression analysis was conducted to characterize the relationship between the EHR vendors selected (MEDITECH, CPSI, Epic, MedHost and other) and hospital location, the type of hospitals, hospitals' practice goal of IE, and the revenue per FTE. Finally logistic regression analysis was conducted to examine the relationship between EHR vendor selection and attainment of Stage 1 meaningful use.

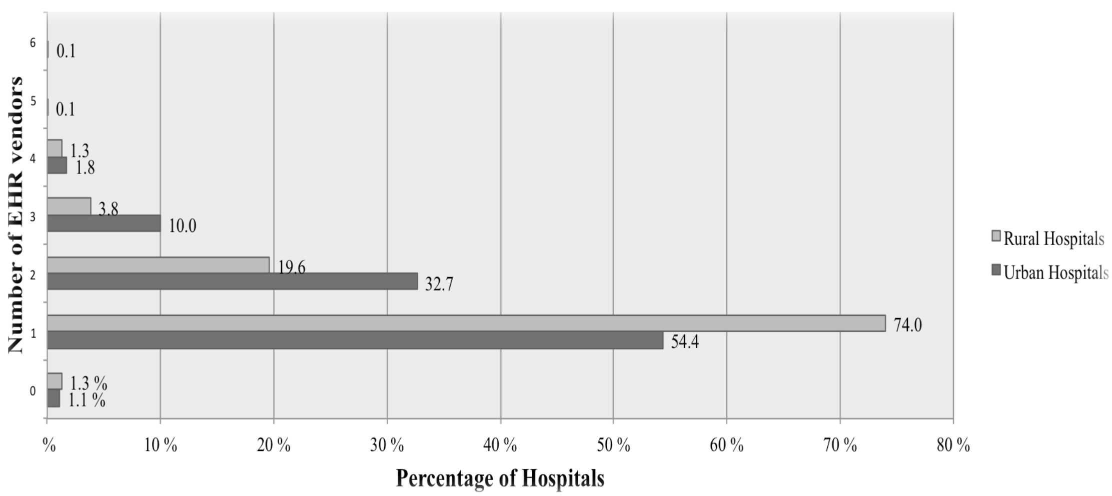
Access to the HIMSS Analytics Database was obtained from HIMSS Analytics by the Texas A&M Health Science Center School of Public Health. This study was reviewed and approved by the Texas A&M University Institutional Review Board (IRB).

Results

Current status of EHR vendors in urban and rural hospitals

Urban hospitals tended to use more different EHR vendors than rural hospitals (Figure 3). The median number of vendors used by both urban and rural hospitals was 1. About half of urban hospitals (54%) used one EHR vendor, while around 3 quarters of rural hospitals (74%) used one EHR vendor within the hospital organization. Around 12 percent of urban hospitals used 3 or 4 different EHR vendors, but only 5 percent of rural hospitals used 3 or 4 different EHR vendors. Very few urban hospitals used more than 5 different EHR vendors, but no rural hospitals used more than 5 different EHR vendors.

Figure 3 Number of EHR vendors per hospital



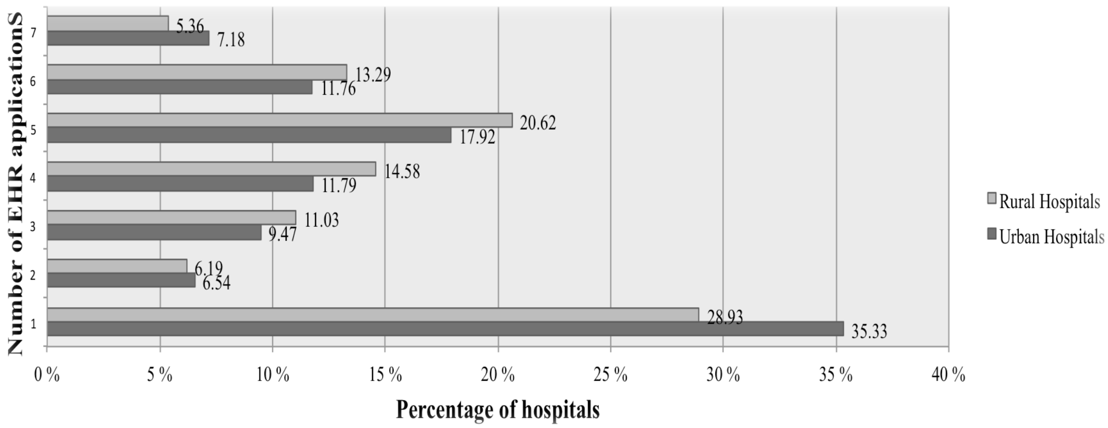
Both urban and rural hospitals used different EHR vendors most with clinical data repository application (Table 4). Patient portal application was the second most application that was tended to go to different EHR vendors for both urban and rural hospitals.

Table 4 Rank of applications using different EHR vendors per hospital

Urban Hospitals				Rural Hospitals			
Rank	Application	Frequency	Percent	Rank	Application	Frequency	Percent
1	Clinical Data Repository	3770	60.0	1	Clinical Data Repository	914	69.0
2	Patient Portal	1057	16.8	2	Patient Portal	181	13.7
3	Clinical Decision Support System (CDSS)	855	13.6	3	Clinical Decision Support System (CDSS)	125	9.4
4	Physician Portal	426	6.8	4	Physician Portal	49	3.7
5	Physician Documentation	64	1.0	5	Order Entry (Includes Order Communications)	39	3.0
6	Order Entry (Includes Order Communications)	58	0.9	6	Computerized Practitioner Order Entry (CPOE)	10	0.8
7	Computerized Practitioner Order Entry (CPOE)	53	0.8	7	Physician Documentation	6	0.5
Total		6283	100	Total		1324	100

Rural hospitals were more likely to use the same EHR vendors for different EHR applications than urban hospitals (Figure 4). Nearly half of urban hospitals (49%) indicated that they used the same EHR vendor for more than 4 different applications. Similarly about half of rural hospitals (54%) indicated that they used the same EHR vendor for more than 4 different applications. About 60 percent (58%) of urban hospitals used the same EHR vendor for more than 3 applications and 65% of rural hospitals used the same EHR vendor for more than 3 applications. The median number of applications for which the same EHR vendor was used was 3, whereas that in rural hospitals was 4.

Figure 4 Number of EHR applications using the same EHR vendor per hospital



The distribution of selected EHR vendors that were used for more than 3 applications differed between urban and rural hospitals (Table 5). The top major 5 EHR vendors accounted for 75% of all EHR vendors selected in urban hospitals and 71% of those in rural hospitals. The top 5 EHR vendors for urban hospitals were Meditech, Cerner, Epic, McKesson, and Medhost and those for rural hospitals were CPSI, Meditech, Healthland, Medhost and Epic. Of these vendors Meditech, Epic, and MedHost were commonly on the list of top 5 EHR vendors for both urban and rural hospitals. The market share of Meditech, CPSI, Epic, and Medhost EHR vendors accounted for more than half of EHR vendors selected by urban hospitals (53%) and by rural hospitals (58%) respectively.

Table 5 Market share of EHRs per location (TOP 10)

Urban Hospitals (N=3652)				Rural Hospitals (N=859)			
	EHR Vendor	Frequency	Percent		EHR Vendor	Frequency	Percent
1	Meditech	864	23.7	1	CPSI	200	23.3
2	Cerner	616	16.9	2	Meditech	147	17.1
3	Epic	596	16.3	3	Healthland	107	12.5
4	McKesson	379	10.4	4	Medhost	82	9.6
5	Medhost	279	7.6	5	Epic	70	8.2
6	Siemens Healthcare	215	5.9	6	Cerner	68	7.9
7	Self-developed	196	5.4	7	McKesson	68	7.9
8	CPSI	185	5.1	8	Siemens Healthcare	33	3.8
9	Allscripts	163	4.5	9	NextGen	27	3.1
10	Other	159	1.4	10	Other	57	1.8
		3652	100			859	100

Relationship between organizational factors and EHR vendor selection

Different organizational factors were associated with hospitals' vendor selection (Table 6). First of all, hospital location was associated with EHR vendor selection. The relative risk ratio for rural hospitals to select CPSI over other EHR vendors was 2.69 ($P<0.001$) and to select Medhost over other EHR vendors was 3.96 ($P<0.001$). In other words, for rural hospitals, the relative risk for selecting CPSI and Medhost relative to other EHR vendors would be expected to increase by a factor of 2.69 and by a factor of 3.96 respectively after adjusting for other factors in the model. However, rural hospitals were less likely to select Epic over other EHR vendors (RRR=0.29, P<0.001) (Table 6).

Type of hospitals also related to EHR vendor selection. Not-for-profit hospitals were less likely than government hospitals to select CPSI (RRR=0.57, P=0.011) and Medhost (RRR=0.49, P=0.037) over other EHR vendors, while for-profit hospitals were more likely than government hospitals to select Meditech (RRR=1.92, P=0.023) over other EHR vendors. As to organizational practice goal-IE initiative, hospitals that had practice goal of IE were more likely to select Epic (RRR=1.55, P<0.001) but were less likely to select Medhost (RRR=0.40, P<0.001) over other EHR vendors. Regarding the relationship between financial resources and vendor selection, given a one unit increase in revenue per FTE, the relative risk of selecting CPSI over other EHR vendors would be 0.87 times more likely. In other words, hospitals with more financial resources would be expected to select other EHR vendors over CPSI (Table 6).

Table 6 Estimates of effect of hospital location and other organizational factors on the EHR vendor selection

	Vendor Selection						
	Not Adjusted				Adjusted Estimate (n=1364)		
	N	RRR	(95% CI)	P-value	RRR	(95% CI)	P-value
Meditech							
Rural	4511	0.82	(0.66-1.01)	0.057	0.88	(0.61-1.26)	0.479
Org Type							
-Government (base)	4340						
-For profit		1.31	(1.03-1.67)	0.029	1.92	(1.10 -3.38)	0.023
- Not for profit		0.96	(0.78-1.17)	0.658	0.84	(0.59-1.18)	0.310
Information Exchange	3690	0.79	(0.66-0.94)	0.010	1.10	(0.81-1.50)	0.525
Revenue per FTE (10k)	1645	0.995	(0.98-1.01)	0.524	0.99	(0.97-1.01)	0.355
CPSI							
Rural	4511	5.19	(4.12-6.53)	<0.001	2.69	(1.76-4.11)	<0.001
Org Type	4340						
-Government (base)							
-For profit		0.27	(0.19-0.38)	<0.001	0.99	(0.42-2.34)	0.981
- Not for profit		0.23	(0.18-0.30)	<0.001	0.57	(0.36-0.88)	0.011
Information Exchange	3690	0.44	(0.66-0.94)	0.010	0.55	(0.37-0.83)	0.005
Revenue per FTE (10k)	1645	0.89	(0.86-0.93)	<0.001	0.87	(0.83-0.92)	<0.001
Epic							
Rural	4511	0.56	(0.43-0.74)	<0.001	0.29	(0.15-0.58)	<0.001
Org Type							
-Government (base)	4340						
-For profit		0.17	(0.09-0.32)	<0.001	1.75e-07	0- .	0.989
- Not for profit		2.48	(1.88-3.27)	<0.001	3.23	(1.69-6.18)	<0.001
Information Exchange	3690	1.48	(1.18-1.84)	0.001	1.55	(1.003-2.39)	0.048
Revenue per FTE (10k)	1645	1.02	(1.002-1.030)	0.030	1.02	(1.00-1.035)	0.080
Medhost							
Rural	4511	1.41	(1.08-1.85)	0.013	3.96	(2.22-7.07)	<0.001
Org Type							
-Government (base)	4340						
-For profit		6.38	(4.48-9.09)	<0.001	7.68	(3.52-16.72)	<0.001
- Not for profit		0.36	(0.24-0.55)	<0.001	0.49	(0.25-0.96)	0.037
Information Exchange	3690	0.09	(0.07-0.12)	<0.001	0.40	(0.23-0.69)	0.001
Revenue per FTE (10k)	1645	1.02	(1.002-1.038)	0.028	1.02	(0.05-0.24)	0.182
Others	(base outcome)						

Relationship between EHR vendor selection and meaningful use attainment

We analyzed the relationship between EHR vendor selection and hospitals' attestation for Stage 1 meaningful use. As shown in Table 7, in urban hospitals we did not find any statistically significant relationship between EHR vendor selection and Stage 1 meaningful use attainment. Whether urban hospitals utilized top 5 EHR vendors or not, it was not statistically associated with their attestation for Stage 1 meaningful use. However, rural hospitals that utilized top 5 EHR vendors were less likely to attain Stage 1 meaningful use than those who utilized other EHR vendors (OR=0.36, P=0.018) (Table 7).

Table 7 Estimates of effect of vendor selection on attainment for Stage 1 meaningful use

	Whether to attain Stage 1 meaningful use			
Variable	N	Odds Ratio	(95% CI)	P-value
Whether to use top 5 EHR vendors in urban hospitals	1564	1.00	(0.72-1.41)	0.983
Whether to use top 5 EHR vendors in rural hospitals	330	0.36	(0.16-0.84)	0.018

Discussion

Results of this study supported two of our hypotheses: 1) rural and urban hospitals select different EHR vendors, 2) organizational contextual factors are associated with EHR vendor selection. We found a very strong link between hospital location and EHR vendor selection. One of the reasons would be EHR vendors' market segmentation strategy. This suggests that hospital location is a component of a vendor's business model. For example, CPSI targets rural, community and critical access hospitals by developing EHR systems to fit their needs. CPSI may understand financial barriers at rural hospitals and develop affordable EHR systems for their targeted customers. As a result, not only rural hospitals but also hospitals with less financial resources tended to select CPSI more over other EHR vendors. Many rural hospitals with less financial resources than urban hospitals may not have any other options but to select affordable CPSI over other expensive EHR vendors. Future research may be conducted about why hospitals selected their current EHR vendors by carrying out intensive interviews with hospitals' leaders who were in charge of EHR vendor selection and implementation.

Our findings suggest that hospitals with different organizational contextual factors such as hospital location, type of hospitals, organizational practice goals and financial resources affect EHR vendor selection. These results may be used by hospitals as a guideline when selecting EHR vendors depending on their organizational characteristics.

To attain Stage 2 meaningful use, EHR vendors must have a capability of exchanging key clinical information. Results of this study suggest that hospitals willing to participate in information exchange initiatives tended to select Epic. However, Epic has a reputation of difficult interoperability and data exchange with other EHR vendors outside of an Epic system. According to a recent study, exchanging clinical data between Epic and other EHR vendors is possible but is very challenging and requires significant effort (KLAS, 2014). Future research also needs to be conducted about whether there would be any change in EHR vendor selection before and after year 2014 when Stage 2 meaningful use that requires clinical information exchange became effective.

We also have to pay attention to the result that did not support our third hypothesis that hospitals in similar location (rural or urban) that selected similar EHR vendors are more likely to succeed in attaining Stage 1 meaningful use. Rural hospitals that selected top 5 EHR vendors in rural areas were less likely to attain Stage 1 meaningful use than those that selected other EHR vendors. As these top 5 EHR vendors are capable of meeting Stage 1 meaningful use and rural hospitals tend to depend mostly on the support of EHR vendors, this disconnection between EHR capability and attainment of meaningful use may be caused by the lack of resources to support end-users' training, implementation of EHRs, and EHR's customization (Ash & Bates, 2005; Boonstra & Broekhuis, 2010). It appears that rural hospitals will face challenges to meet meaningful use without additional funding support. Further studies may be conducted to examine reasons why rural hospitals failed to attain meaningful use, even though they selected certified EHR vendors that had capabilities of attaining meaningful use as other many rural hospitals selected.

This study had several limitations. First, the design of this study is cross-sectional. Even though we identified relationships between EHR vendor selection and organizational contextual factors, these results may not provide cause-and-effect relationship. In addition, we have included only Meditech, CPSI, Epic, MedHost and other as unique categories in our model. This was because there were too many different vendors to include all as unique categories in the model. Even though we tried to use coding convention that included representative EHR vendors, this may lead to potential bias in determining the relationship between vendor selection and organizational contextual factors identified in this study. Finally, the sample size to examine the relationship between EHR vendor selection and attainment for Stage 1 meaningful use was relatively small. Only 41 percent of hospitals answered the question regarding the attestation for Stage 1 meaningful use. Even though hospitals that did not answer this question seemed not to have attained Stage 1 meaningful use, this small sample size may lead to potential bias in finalizing the relationship between EHR vendor selection and attainment for Stage 1 meaningful use.

Conclusion

Hospital location is associated with EHR vendor selection. Rural and urban hospitals intended to select different EHR vendors. Other organizational contextual factors such as type of hospitals, organizational practice goals, and financial resources also are associated with EHR vendor selection. They may be the result of vendor target marketing efforts. They may be the result of vendor target marketing efforts. They may be the result of hospital alignment with vendor offerings, or a combination of both. Even though rural hospitals selected EHR vendors that are capable of meeting meaningful use, they still face challenges in attaining meaningful use. Supports to educate end users or to implement EHR systems in rural hospitals are required.

CHAPTER IV

DESIGNING SUCCESSFUL ELECTRONIC HEALTH RECORDS IMPLEMENTATION STRATEGIES ACROSS DIFFERENT JOB CATEGORIES

Background and Significance

Electronic health records (EHR) are widely recognized as an essential element to improving quality and efficiency in health care (Wu et al., 2006). Spurred by government initiative such as the Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009 (HHS, 2009), which provides incentive payments for EHR use, many hospitals have begun to implement EHR systems (Blumenthal, 2010). However, EHR adoption continues at a slow pace (Boonstra & Broekhuis, 2010; Jha et al., 2009). EHR implementation requires people to change the way they work and often leads to worker stress. Often-cited barriers to EHR implementation include attitudinal and behavioral issues, often summarized as an end-user's inability to use or resistance to using EHR systems, as well as a lack of organizational support in assisting with EHR implementation (Bhattacherjee & Hikmet, 2007; Hostgaard & Nohr, 2004; Jha et al., 2009).

Designing an EHR implementation strategy tailored to the expectations and satisfaction of various categories of end-users has received little attention despite its potential importance to successful EHR implementation. In fact, few studies have assessed the relationship between different job categories of end-users' and their expectations or satisfaction regarding EHRs. Because end-users' roles and responsibilities vary, EHRs support and contribute to their work in different ways

(Dansky et al., 1998; Gamm et al., 1998). These varying roles and responsibilities affect end-user expectations and the ways in which EHRs serve to end-users' job responsibilities affect their satisfaction with EHRs and, ultimately, EHR acceptance.

Following the work of Davis, the Technology Acceptance Model (TAM) helps explain end-users' acceptance of EHRs, which is one way to represent the effectiveness of EHR implementation (Davis, 1989). According to the TAM, perceived usefulness and perceived ease of use determine whether end-users accept EHRs (Chuttur, 2009; Davis, 1989; Davis, Bagozzi, & Warshaw, 1989). Perceived usefulness refers to the degree to which end-users believe that using an EHR will help them improve their job performance. Perceived ease of use refers to the degree to which end-users believe that using an EHR will be easy and require little additional effort (Davis, 1989). These two main variables lead end-users to either accept or reject EHRs. Characterized by varying job tasks, different job categories may affect end-users' perceived usefulness of EHRs and their perceived ease of EHR use. Therefore, designing EHR implementation and adoption strategies according to end-user expectations is important because they will affect their perceived usefulness and ease of use of EHRs, which is closely related to EHR adoption.

In the same vein, the Healthcare Information and Management Systems Society (HIMSS) emphasizes EHR usability for successful EHR implementation. According to the HIMSS, EHR usability involves both efficiency in performing specific tasks and end-user satisfaction with EHRs (HIMSS, 2009). This concept of usability is closely related to the perceived usefulness and perceived ease of use suggested by the TAM model. Andersen and Aday's behavioral model also helps describe the importance of perceived and evaluated needs for accepting EHR use (Aday & Andersen, 1974). Predisposing characteristics such as different end-user job categories will influence end-users' perceived needs-represented by perceived usefulness and perceived ease of use-and eventually have an impact on EHR utilization (Aday & Andersen, 1974).

Recognizing the importance of the relationship between different end-user perception and end-user acceptance in successfully implementing an EHR system, this study aimed to evaluate how EHRs contribute differently to end-user job performance and perceptions across various job categories of health care organizations and to identify critical elements that affect end-user satisfaction with EHRs. In this study we tested our hypotheses that: 1) EHR contributions to end-user work processes differ according to job categories (provider, other clinical or nonclinical); 2) end-users' perceived usefulness and perceived ease of use of EHRs affect their satisfaction with EHRs; and 3) variations in organizational support when implementing an EHR system influences end-user satisfaction with EHRs.

Materials and Methods

Data

We used primary data from surveys conducted between March and June 2011 with the staff members across different job categories at four sites within one integrated health care system in Texas. These four sites were selected because of their involvement in EHR implementation. An online questionnaire asked various categories of EHR end-users to self-report their personal characteristics and perceptions toward EHRs and EHR implementation, including organizational support, training, and EHRs' impact on their job activities. Distributed to 776 staff members, including physicians, physician assistants, nurse practitioners, nurses, other clinical staff, front desk/clerical staff, and administrator/managers, it received a response rate of 44% across the four clinics.

This online survey was conducted as part of a research project of the National Science Foundation-funded Center for Health Organization Transformation (CHOT) at the Texas A&M Health Science Center. This study was reviewed and approved by the Texas A&M University Institutional Review Board (IRB).

Sample

Our sample for analysis consisted of 339 staff members across different job categories who responded to the survey (Table 8). We categorized the jobs into three categories: provider, other clinical, or nonclinical. We included physicians, physician assistants, and nurse practitioners in the "provider" category; nurses (registered nurses, licensed vocational nurses), and other clinical staff (medical assistants, technicians, etc.) in the "other clinical" category; and administrators/managers and front desk/clerical staff in the "nonclinical" category.

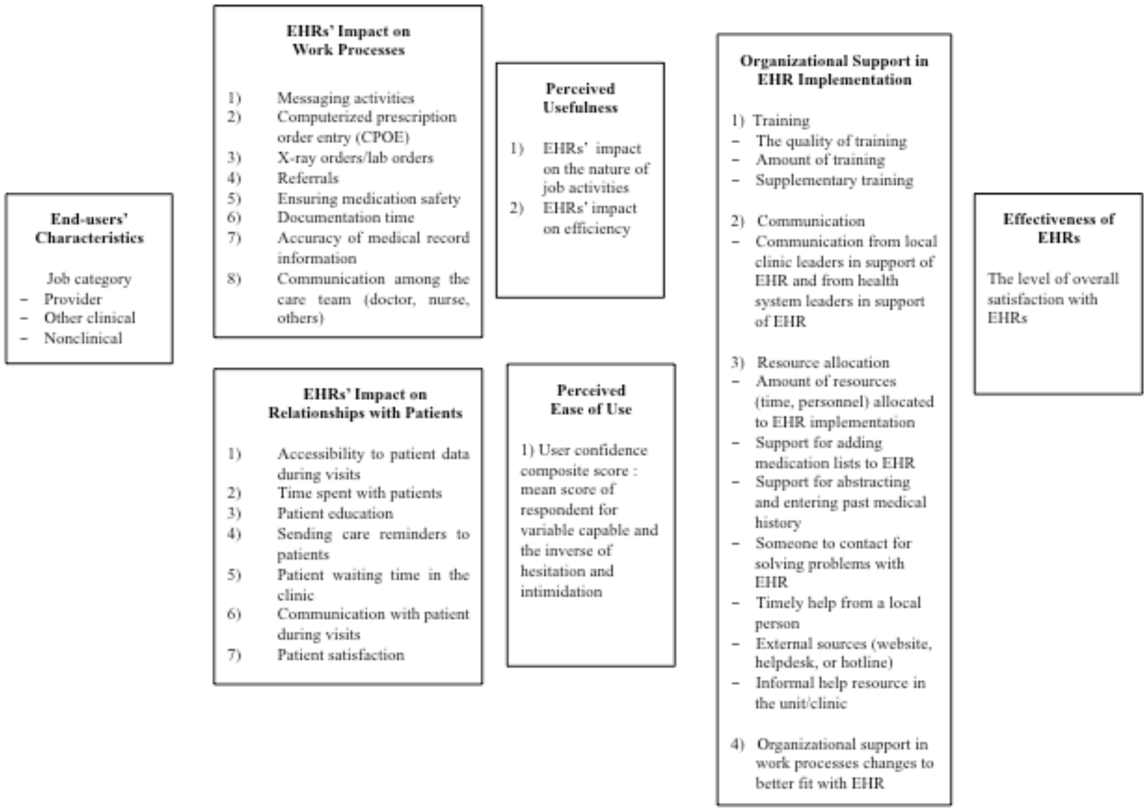
Table 8 Demographics

Total			339	100%
Job Category	Provider	Physician	70	20.65%
		Physician Assistant	9	2.65%
		Nurse Practitioner	5	1.47%
	Other Clinical	Nurse (RN, LVN)	92	27.14%
		Other Clinical Staff (MAs,Techs, etc.)	74	21.83%
	Non-clinical	Front Desk/Clerical Staff	66	19.47%
		Administrator/Manager	23	6.78%
Gender	Male		67	19.76%
	Female		272	80.24%
Age	Under 22		3	0.88%
	22-25		41	12.90%
	26-30		39	11.50%
	31-40		106	31.27%
	41-50		81	23.89%
	51-60		49	14.45%
	61 and above		20	5.90%

Analysis model using survey questions

All the staff members were asked to respond to the questions shown in our analysis model (Figure 5). In addition to questions relating to personal characteristics such as job categories, age, and gender, respondents were asked to rate their satisfaction with EHRs or with organizational support on a five-point Likert scale as *very dissatisfied, dissatisfied, neutral, satisfied, or very satisfied*; or, for some questions as *strongly disagree, disagree, neutral, agree or strongly agree*. Similarly, responses to questions asking about EHRs' impact on job activities, relationships with patients and the perceived usefulness of EHRs were coded via a five-point Likert scale as *very negative impact, negative impact, no impact, positive impact, or very positive impact*. Responses to questions asking other perspectives on end users' experience with EHR implementation were coded via a five-point Likert scale as *strongly disagree, disagree, neutral, agree or strongly agree*.

Figure 5 Analysis Model



Information-theoretic analysis of survey data using normalized mutual information

We quantitatively analyzed the relationship between end-users' perceived usefulness of EHRs and their perception toward EHRs' impact on work processes and patient relationships based on an information-theoretic approach using a metric called the normalized mutual information (NMI). We also used the NMI to identify elements influencing end-users' overall satisfaction with EHRs. The mutual information (MI) is a symmetric metric that measures the mutual dependency between two random variables. The concept of MI is rooted in information theory, which has been formally established by Shannon and provides the theoretical foundations of digital communications and digital encoding of data (Shannon, 2001).

Conceptually, the MI between two variables measures how much information one variable provides about the other (and vice versa, due to symmetry). The NMI is obtained by normalizing the MI by the maximum possible amount of information that one variable may provide about the other. The MI may be normalized in different ways (Xuan, Julien, Wales, & Bailey, 2010), and in the current study, the NMI between two random variables *X* and *Y* was computed using the following formula (Kvalseth, 1987; Liu, Guo, & Tan, 2008):

$$NMI(X;Y) = \frac{I(X;Y)}{\min(H(X), H(Y))}$$

I(X;Y) is the MI between *X* and *Y*, *H(X)* is the entropy (i.e., the information content) of *X*, and *H(Y)* is the entropy of *Y*, where all three quantities are typically measured in "bits." The above normalization method guarantees that the NMI lies between 0 and 1.

The entropy *H(X)* of a discrete random variable *X* can be computed from its probability distribution (i.e., probability mass function) as follows (Cover & Thomas, 2012):

$$H(X) = \sum_x p(x) \log \frac{1}{p(x)}$$

where *p(x)* is the probability that the random variable will take the value *X*=*x*. The entropy *H(X)* measures the amount of information in the random variable *X*, in terms of how many bits are needed on average to encode the value of *X*. Given the knowledge of another discrete random variable Y, one can also compute the conditional entropy $H(X|Y)$ of X given Y, which is defined as follows (Cover & Thomas, 2012):

$$H(X|Y) = \sum_{x,y} p(x,y) \log \frac{p(y)}{p(x,y)}$$

where $p(x,y)$ is the joint probability that $X=x$ and $Y=y$, and $p(y)$ is the probability that $Y=y$. The conditional entropy $H(X|Y)$ measures the remaining amount of information that X still contains when Y is completely known. The MI $I(X;Y)$ is computed by $I(X;Y) = H(X) - H(X|Y)$ as the difference between the entropy $H(X)$ of the random variable X and the conditional entropy $H(X|Y)$ of X when the other random variable Y is given (Cover & Thomas, 2012). Using the previous definitions of $H(X)$ and $H(X|Y)$, the mutual information $I(X;Y)$ between the random variables X and Y can be computed by

$$I(X;Y) = \sum_{x,y} p(x,y) \log \frac{p(x,y)}{p(x)p(y)}$$

Conceptually, $I(X;Y)$ measures how much information one has about a random variable X if one has complete knowledge of another random variable Y. The mutual information $I(X;Y) = H(X) - H(X|Y)$ measures the amount of shared information between X and Y by estimating the average number of bits that would be "reduced" for encoding X if Y is given. Equivalently, we can measure the mutual information by $I(X;Y) = H(Y) - H(Y|X)$, by quantifying the amount of information in Y that can be given by X.

Based on the definition $I(X;Y) = H(X) - H(X|Y) = H(Y) - H(Y|X)$, we can make several important observations. First, because the (conditional) entropy of a random variable cannot be negative, we have $I(X;Y) \leq H(X)$ and $I(X;Y) \leq H(Y)$, hence the MI cannot exceed the lesser of $H(X)$ and $H(Y)$. In other words, the amount of "shared" information between X and Y cannot be larger than the amount of information in either variable. Next, we can also see that $I(X;Y)$ has to be nonnegative because the conditional entropy $H(X|Y)$ of X cannot be larger than the original entropy $H(X)$ and $H(Y|X)$ cannot be larger than $H(Y)$. This is intuitive if we consider the fact that $H(X|Y)$ measures the "remaining" amount of information contained in X when Y is fully known, because whatever information remains cannot exceed the original information content. Furthermore, we can also see that the MI is $I(X;Y) = 0$ if the two variables are independent, because $H(X) = H(X|Y)$ and $H(Y) = H(Y|X)$; neither X nor Y contains any information about the other. Finally, we can also see that $I(X;Y)$ will reach its maximum value when one of the random variables is completely dependent on the other variable. For example, if X is completely dependent on Y, we have $H(X|Y) = 0$ because there is no information remains in X if Y is already known, in which case the MI will be simply $I(X;Y) = H(X) - H(X|Y) = H(X)$.

Because the mutual information $I(X;Y)$ is nonnegative and cannot exceed the minimum of $H(X)$ and $H(Y)$, $NMI(X,Y)$ will take a value between 0 and 1 as mentioned before. An NMI of 0 implies that the two random variables are completely independent. On the other hand, the NMI will be 1 when either variable (with smaller entropy) is completely dependent on the other variable (with larger entropy). Unlike the traditionally used correlation coefficient, the NMI does not assume a linear relationship between variables, and therefore, we need not make any distributional assumptions.

Furthermore, it can be directly used for analyzing categorical data, without the need to first translate a binary response or Likert scale into numerical values for analysis.

Analytic approach

To understand end-users' general perceptions toward EHR systems, we first examined EHRs' impact on work processes and on relationships with patients using the means by 3 different job categories (provider, other clinical, nonclinical).

To test our first hypothesis, we calculated the NMI between EHRs' impact on various job activities and end-users' perceived usefulness of EHRs (EHRs' impact on the nature of job activity and efficiency). To ease our interpretation, we ranked job activities based on the calculated NMI and summarized the results for each job category (provider, other clinical, or nonclinical). This was to determine which job activities more related more closely to end-users' perceived usefulness of EHRs across different job categories. We included eight variables representing EHRs' impact on work processes variables and seven variables representing EHRs' impact on relationships with patients (Figure 1). To facilitate the comparison between the NMI and the traditional method of association, we also calculated the Pearson correlation coefficients (PCC) between these variables.

To test our second hypothesis, we calculated the NMI between various variables of organizational support and end-users' overall satisfaction with EHRs. We excluded personal characteristics, such as age and gender, in our analysis because these variables were unchangeable and unimprovable. We ranked the variables based on the calculated

NMI and summarized the results according to three job categories (provider, other clinical and nonclinical). This aided in identifying critical elements more closely associated with the level of satisfaction with EHRs across the three different job categories. To facilitate the comparison between the NMI and the traditional method of association we also calculated the Pearson correlation coefficients (PCC) between these variables.

Results

General end-user perceptions toward EHRs

Among the three job categories, providers tended to respond negatively, and nonclinical staff tended to respond positively to more items (Table 9). The overall mean of satisfaction with an EHR system across three job categories in our sample was 2.98 suggesting neither dissatisfaction nor satisfaction. Providers showed the lowest level of satisfaction with EHRs (2.17) while nonclinical staff members showed the highest level of satisfaction with EHRs (3.42) among the three job categories. Providers displayed the most negative thoughts on EHRs' impact on documentation time (1.87) and on their own work efficiency (2.00). Generally, other clinical and nonclinical staff members viewed EHRs in a positive way. Both other clinical and nonclinical staff members showed the highest score on EHRs' impact on referrals (3.81, 4.01). They also viewed an EHR system as having the most positive impact on accessibility to patient data during visits (3.88, 3.39).

Table 9 Means of end-user perceptions toward EHRs

	Provider (n=85)	**Other Clinical (n=166)**	**Nonclinical (n=88)**	**Overall Mean (n=339)**
Overall satisfaction with EHRs	2.17	3.17	3.42	2.98
EHRs' impact on work processes				
Messaging activities	3.10	3.50	3.75	3.46
CPOE	3.63	3.63	3.68	3.66
X-ray orders/lab orders	2.85	3.33	3.56	3.25
Referrals	3.33	3.81	4.01	3.73
Ensuring medication safety	3.13	3.54	3.75	3.44
Documentation time	1.87	3.17	3.72	2.94
Accuracy of medical record information	2.80	3.42	3.79	3.34
Communication among the care team (doctor, nurse, others)	2.98	3.56	3.74	3.46
EHRs' impact on relationships with patients				
Accessibility to patient data during visits	2.63	3.61	3.88	3.39
Time spent with patients	2.18	3.28	3.51	3.00
Patient education	2.79	3.45	3.66	3.29
Sending care reminders to patients	2.84	3.24	3.41	3.15
Patient waiting time in the clinic	2.34	3.11	3.33	2.91
Communication with patients during visits	2.54	3.45	3.54	3.19
Patient satisfaction	2.82	3.33	3.60	3.25
EHRs' impact on the nature of end users' job activities	2.39	3.35	3.70	3.20
EHRs' impact on efficiency	2.00	3.31	3.69	3.07

Relationship between EHRs' impact on specific job activities and EHRs' overall impact on the nature of job activities

The distribution of ranks of EHRs' impact on specific job activities influencing EHRs' impact on the nature of job activities based on NMI scores differed according to job categories (Table 10). Among providers, EHRs' impact on the nature of their job activities depended most on their assessment of how EHRs affected relationships with patients, such as patient satisfaction (0.2769), time spent with patients (0.2767), patient waiting time in the clinic (0.2461), and accessibility to patient data during visits (0.2402). Among clinical staff members, EHRs' impact on the nature of their job activities depended most on their assessment of how EHRs affected the accuracy of medical record information (0.3102), documentation time (0.3082), messaging activities (0.3064), and patient satisfaction (0.2881). Among nonclinical staff members, EHRs' impact on the nature of their job activities depended most on their assessment of how EHRs affected work processes such as communication among the care team (0.3545), patient satisfaction (0.3285), documentation time (0.3056), messaging activities (0.2661) and referrals (0.2501).

For both providers and other clinical staff members, X-ray/lab orders and sending care reminders to patients were the job activities feeling the least impact from EHR use. Even though the rankings of computerized physician order entry (CPOE) differed by job categories, it ranked relatively lower than other job activities for all of three job categories (Table 10).

Table 10 Dependencies between EHRs' impact on the specific job activities and EHRs' impact on the nature of job activities by job categories

Ranking	Provider			Other Clinical			Nonclinical		
	Job activity	NMI*1)	PCC*2)	Job activity	NMI	PCC	Job activity	NMI	PCC
1	Patient satisfaction	0.2769	0.46	Accuracy of medical record information	0.3102	0.65	Communication among the care team (doctor, nurse, others)	0.3545	0.72
2	Time spent with patient	0.2767	0.60	Documentation time	0.3082	0.65	Patient satisfaction	0.3285	0.72
3	Messaging activities	0.2479	0.55	Messaging activities	0.3064	0.75	Documentation time	0.3056	0.76
4	Patient waiting time in clinic	0.2461	0.50	Patient satisfaction	0.2881	0.66	Messaging activities	0.2661	0.68
5	Accessibility to patient data during visit	0.2402	0.52	Communication with patient during visit	0.2839	0.65	Referrals	0.2501	0.58
6	Patient education	0.2285	0.41	Patient education	0.2730	0.62	Time spent with patient	0.2313	0.71
7	Documentation time	0.2267	0.49	Ensuring medication safety	0.2680	0.65	Accuracy of medical record information	0.2265	0.54
8	Communication with patient during visit	0.1968	0.48	Accessibility to patient data during visit	0.2633	0.68	Sending care reminders to patients	0.1776	0.43
9	Referrals	0.1966	0.51	Time spent with patient	0.2615	0.65	X ray/lab orders	0.1751	0.57
10	Communication among the care team (doctor, nurse, others)	0.1752	0.51	Communication among the care team (doctor, nurse, others)	0.2557	0.66	Patient waiting time in clinic	0.1643	0.51
11	CPOE	0.1706	0.35	Referrals	0.2179	0.61	Accessibility to patient data during visit	0.1585	0.54
12	Ensuring medication safety	0.1630	0.35	Patient waiting time in clinic	0.2059	0.57	Communication with patient during visit	0.1542	0.63
13	Accuracy of medical record information	0.1616	0.44	CPOE	0.1782	0.58	Patient education	0.1419	0.59
14	X ray/lab orders	0.1418	0.49	X ray/lab orders	0.1590	0.56	Ensuring medication safety	0.1308	0.17
15	Sending care reminders to patients	0.1392	0.39	Sending care reminders to patients	0.1409	0.56	CPOE	0.1085	0.05

*1) NMI: Normalized mutual information
*2) PCC: Pearson correlation coefficient

Relationship between EHRs' impact on specific job activities and EHRs' overall impact on job efficiency

The distribution of dependencies between EHRs' impact on specific job activities and EHRs' impact on job efficiency, based on NMI scores, differed according to job categories (Table 11). Patient waiting time (0.2218) in the clinic for providers, documentation time (0.3462) for other clinical staff, and communication among the care team (0.3915) were the most closely associated with EHRs' impact on job efficiency. Other job activities having a strong relationship (top 5) with EHRs' impact on the nature of job activity included accessibility to patient data during visits (0.2199), time spent with patients (0.1948), documentation time (0.1813), and accuracy of medical record information (0.1779) for providers; accuracy of medical record information (0.3301), time spent with patients (0.3149), patient satisfaction (0.3049) and ensuring medication safety (0.2987) for other clinical staff; and documentation time (0.3802), patient satisfaction (0.2712), messaging activities (0.2526), and accuracy of medical record information (0.2526) for nonclinical staff (Table 11).

Table 11 Dependencies between EHRs' impact on specific job activities and EHRs' impact on efficiency by job categories

Ranking	Provider			Other Clinical			Nonclinical		
	Job activity	NMI*1)	PCC*2)	Job activity	NMI	PCC	Job activity	NMI	PCC
1	Patient waiting time in clinic	0.2218	0.53	Documentation time	0.3462	0.69	Communication among the care team (doctor,nurse,others)	0.3915	0.71
2	Accessibility to patient data during visit	0.2199	0.46	Accuracy of medical record information	0.3301	0.67	Documentation time	0.3802	0.82
3	Time spent with patient	0.1948	0.52	Time spent with patient	0.3149	0.73	Patient satisfaction	0.2712	0.71
4	Documentation time	0.1813	0.50	Patient satisfaction	0.3049	0.71	Messaging activities	0.2526	0.66
5	Accuracy of medical record information	0.1779	0.40	Ensuring medication safety	0.2987	0.61	Accuracy of medical record information	0.2521	0.58
6	Messaging activities	0.1725	0.40	Communication with patient during visit	0.2716	0.64	Referrals	0.2471	0.62
7	Referrals	0.1686	0.37	Communication among the care team (doctor,nurse,others)	0.2665	0.66	Time spent with patient	0.2311	0.76
8	Communication among the care team (doctor,nurse,others)	0.1605	0.41	Accessibility to patient data during visit	0.2644	0.68	X ray/lab orders	0.1753	0.58
9	Patient satisfaction	0.1564	0.39	Patient education	0.2507	0.60	Sending care reminders to patients	0.1746	0.50
10	X ray/lab orders	0.1551	0.40	Messaging activities	0.2495	0.68	Patient waiting time in clinic	0.1711	0.54
11	CPOE	0.1481	0.30	Patient waiting time in clinic	0.2152	0.62	Ensuring medication safety	0.1638	0.30
12	Communication with patient during visit	0.1430	0.42	X ray/lab orders	0.2071	0.60	Patient education	0.1621	0.67
13	Patient education	0.1365	0.31	Referrals	0.1922	0.60	Accessibility to patient data during visit	0.1494	0.58
14	Ensuring medication safety	0.1305	0.28	CPOE	0.1472	0.51	Communication with patient during visit	0.1403	0.63
15	Sending care reminders to patients	0.1141	0.36	Sending care reminders to patients	0.1470	0.51	CPOE	0.1144	0.02

*1) NMI: Normalized mutual information
*2) PCC: Pearson correlation coefficient

Elements related to end-users' satisfaction with EHRs

Even though the critical elements relating to end-users' satisfaction with an EHR system differed across the three job categories, end-users' perceived usefulness of EHRs (EHRs' impact on the nature of job activities and on efficiency) proved to be the most critical element for all three job categories (Table 12).

Satisfaction with the quality of training rather than the amount of training was more closely associated with satisfaction with EHRs for providers and other clinical staff. NMI scores for satisfaction with the quality of training were 0.183 and 0.2256 for providers and other clinical members, respectively. For nonclinical staff, organizational support in making work processes to better fit with EHRs (0.3004) and communication with organizational leaders (0.2789) influenced their satisfaction with EHRs more than the quality of training or the amount of training. For all the staff members, satisfaction with EHRs depended less on informal help among end-users in units/clinics with EHR systems than other elements.

Table 12 Critical elements that relate to the levels of end-users' overall satisfaction with EHRs by job categories

Ranking	Provider			Other Clinical			Nonclinical		
	Element	NMI*1)	PCC*2)	Element	NMI	PCC	Element	NMI	PCC
1	Impact on nature of my job activities	0.3538	0.69	Impact on my efficiency	0.3510	0.79	Impact on nature of my job activities	0.4680	0.81
2	Impact on my efficiency	0.2580	0.64	Impact on nature of my job activities	0.3366	0.77	Impact on my efficiency	0.4480	0.80
3	User confidence	0.2446	0.33	Satisfaction with the quality of training for EHR	0.2256	0.66	User confidence	0.3164	0.34
4	Satisfaction with the quality of training for EHR	0.1830	0.53	*The level of* contact person when encountering a problem using EHR	0.2239	0.56	The level of organizational support in making changes to work processes to better fit with EHR	0.3004	0.64
5	Satisfaction with support for adding medication lists to EHR system	0.1699	0.27	Satisfaction with amount of resources (time, personal) allocated to EHR implementation	0.2033	0.60	Satisfaction with communication from healthcare system leaders in support of EHR implementation	0.2789	0.63
6	Satisfaction with communication from local clinic leaders in support of EHR implementation	0.1522	0.41	*The level of* timely help from a local person when encountering a problem using EHR	0.1959	0.62	Satisfaction with amount of supplementary training	0.2755	0.52
7	*The level of* timely help from a local person when encountering a problem using EHR	0.1483	0.38	User Confidence	0.1927	0.51	Satisfaction with communication from local clinic leaders in support of EHR implementation	0.2364	0.57
8	*The level of* organizational support in making changes to work processes to better fit with EHR	0.1325	0.38	Satisfaction with communication from healthcare system leaders in support of EHR implementation	0.1886	0.61	Satisfaction with the quality of training for EHR	0.2302	0.59
9	Satisfaction with amount of training for EHR	0.1161	0.37	Satisfaction with support for abstracting and entering past medical history	0.1820	0.61	*The level of* contact person when encountering a problem using EHR	0.2094	0.53
10	*The level of* useful external sources (website, helpdesk, or hotline) available when encountering a problem using EHR	0.1155	0.31	Satisfaction with support for adding medication lists to EHR system	0.1782	0.52	Satisfaction with amount of resources (time, personal) allocated to EHR implementation	0.1955	0.43
11	Satisfaction with communication from healthcare system leaders in support of EHR implementation	0.1065	0.38	Satisfaction with communication from local clinic leaders in support of EHR implementation	0.1690	0.59	*The level of* useful external sources (website, helpdesk, or hotline) available when encountering a problem using EHR	0.1947	0.43
12	Satisfaction with amount of supplementary training	0.1055	0.33	*The level of* organizational support in making changes to work processes to better fit with EHR	0.1674	0.58	Satisfaction with support for adding medication lists to EHR system	0.1816	0.45
13	*The level of* contact person when encountering a problem using EHR	0.1003	0.22	Satisfaction with amount of supplementary training	0.1633	0.56	Satisfaction with support for abstracting and entering past medical history	0.1611	0.48
14	*The level of* informal help among end users in unit/clinic with EHR	0.0808	0.29	*The level of* useful external sources (website, helpdesk, or hotline) available when encountering a problem using EHR	0.1363	0.48	*The level of* informal help among end users in unit/clinic with EHR	0.1323	0.28
15	Satisfaction with support for abstracting and entering past medical history	0.0729	0.16	*The level of* informal help among end users in unit/clinic with EHR	0.1193	0.18	*The level of* timely help from a local person when encountering a problem using EHR	0.1269	0.31

*1) NMI: Normalized mutual information*2) PCC: Pearson correlation coefficient

Discussion

The results of this study supported all of our hypotheses: 1) EHRs contribute to the job activities of end-users in different ways depending on job categories (provider, other clinical or nonclinical); 2) end-users' perceived usefulness and perceived ease of use toward EHRs are related to their satisfaction with EHRs; and 3) various organizational support have an impact on end-users' satisfaction with EHRs. These findings suggested that end-users across different job categories in health care organizations view EHRs' impact on their job activities differently. As a result, these differing perceptions toward EHRs influence end-users' perceived usefulness of EHRs, and, ultimately, their satisfaction with EHRs. This implies that health care leaders and policy makers need to devote their resources and effort to EHR implementation and adoption after designing EHR implementation strategies customized to end-users in different job categories.

Our analysis focused primarily on elements that health care managers can improve and that may affect end-user acceptance and effectiveness of EHRs. To that end, health care leaders who are involved in EHR implementation can strengthen several things, as reflected and summarized in the ranks of elements, associated with end-users' satisfaction with EHRs. First, health care leaders need to determine how an EHR system contributes to end-users in different job categories and emphasize those job activities on which EHRs have the highest positive impact. For example, according to providers using EHRs, patient satisfaction was the most critical job activity influencing the nature of providers' job activities, and patient waiting time was the most critical job activity influencing providers' job efficiencies. If providers recognize the positive impact that EHRs make on patient satisfaction and patient waiting time, this will increase their perceived usefulness of EHRs and eventually increase their satisfaction with EHRs. Second, health care leaders can increase EHR acceptance by providing high-quality of EHR training for end-users. These leaders may need to provide high-quality EHR training by customizing it to end-users' job activities. Such training may increase end-users' ease of use of EHRs, represented as user confidence in this study and closely associated with end-users' satisfaction with EHRs. Third, health care leaders need to provide sufficient organizational support and resources for EHR implementation and offer end-users help for a smooth transition into new systems without being overly burdened.

Like other existing literatures, our study confirmed the importance of training, leaders' involvement, and resource allocation when implementing an EHR system, one of organizational changes (McGinn et al., 2011). In addition, this study documented how EHRs contribute to staff members with varying sets of tasks. It also identified critical elements relating to the levels of EHR effectiveness across different job categories. This study will help health care organization leaders design successful and customized EHR implementation strategies that depend on different job categories. Our study findings refine an EHR implementation model, suggesting that health care leaders need to rethink the ways they design EHR implementation strategies. To increase the effectiveness of EHRs, health care leaders need to customize and prioritize their resources and efforts according to end-user expectations and vary EHR implementation strategies across different job categories instead of applying one uniform strategy to all end-users.

We first adopted a novel analytic approach that used NMI to investigate the relationships among variables in the study, considering two variables at a time (Kvalseth, 1987; Shannon, 2001; Xuan et al., 2010). The main motivation for utilizing NMI in our study was that, unlike the traditional correlation coefficient, the NMI can measure dependencies between random variables without making any specific assumptions about the underlying distributions or the linearity (or nonlinearity) of their relationship. Moreover, the NMI can be directly applied to the analysis of categorical data without the need to translate categorical values into numerical values, thereby avoiding any unwanted artifacts that such translation may introduce. The correlation method, which measures the linear dependence between two random variables, is the most commonly used for predicting and describing the relationship among random variables due to its relatively easy and simple computation. However, the correlation is not equivalent to dependence because independent variables are uncorrelated with 0 for their correlation coefficient, but uncorrelated variables are not necessarily independent. In addition, a correlation coefficient requires some assumptions and probability distributions regarding random variables (Battiti, 1994; Grimmett & Stirzaker, 1992).

This study had several limitations. First, because its design was cross-sectional, the results may not provide cause-and-effect relationships, and because the survey was conducted in the early stages of an EHR implementation, people's views on the implementation may have changed later. Second, the survey was designed as an online self-report. Even though we used a five-point Likert scale instead of open questions or yes or no questions to collect more accurate responses, there is always concern over the reliability of survey responses. It is possible that responses were biased by the fluctuating feelings of the respondents at the time they responded to the survey. Third, the sample in this study was limited to one health care organization in Texas. Even though we included four different sites within one integrated health care organization, Texas' health care environment may differ from other states. This may lead to difficulties in generalizing the results of this study to all other hospitals in the United States.

Conclusion

An EHR system support and contribute to the work of end-users differently according to staff roles and responsibilities. Varying staff roles and responsibilities related to end-users' perceived usefulness and perceived ease of use of EHRs, which were closely associated with their satisfaction with EHRs. In addition, various organizational supports in assisting in EHR implementation, including end-user training and resource allocation, were closely associated with the level of effectiveness of EHR implementation. This study will help health care organization leaders design more successful strategies when implementing an EHR system across different job categories within health care organizations.

CHAPTER V

CONCLUSIONS

Discernable differences exist in EHR implementation and adoption between rural and urban hospitals and among end-users across different job categories. First, rural hospitals lag behind urban hospitals in EHR adoption and struggle with attaining meaningful use. Due to limited resources available in rural hospitals, modified and differentiated time schedules of meaningful use and focused EHR implementation strategies, in addition to other organizational change-related efforts identified in this research, are necessary to facilitate EHR implementation and the readiness for meaningful use in rural hospitals.

Second, rural and urban hospitals select different EHR vendors. In addition to hospital location, type of hospitals, financial resources, and hospital practice goals are associated with EHR vendor selection. In rural hospitals, we found a disconnection between EHR vendor selection and attaining meaningful use. Even though rural hospitals use EHR vendors that are capable of meeting meaningful use, they still face challenges in attaining meaningful use.

Third, EHRs support and contribute to the work of end-users differently according to their roles and responsibilities. In turn, this related to end-users' perceived usefulness and perceived ease of EHR use, which influence their satisfaction with EHR systems. Our study also identified various organizational supports provided throughout EHR implementation, including end-user training and resources, strongly associated with the levels of perceived effectiveness of EHRs.

Overall, this study will help health care managers design more successful strategies for implementing EHR systems tailored to their organizations, and their employees' job categories. To increase EHR systems effectiveness, health care leaders need to consider their organizational contexts and end-users' expectations that vary across different job categories and customize and prioritize their resources and efforts instead of applying one uniform EHR implementation strategy to all organizations. Policy makers and health care organization leaders must pay special attention to EHR implementation and adoption strategies in rural hospitals, which currently struggle to attain meaningful use criteria.

Future studies may be conducted about how hospitals system affiliations relate to EHR implementation, EHR vendor selection and attainment of meaningful use. System-affiliated rural hospitals may have more resources to purchase customized EHRs and educate end-users than stand-alone rural hospitals. Rural hospitals that are part of larger and multilevel health care systems have different organizational contexts caused by economies of scale. This may lead to differences in EHR implementation and attainment of meaningful use among rural hospitals.

Future studies may also be conducted about relationships between hospitals and EHR vendors. Hospitals' adaptability to EHR vendors as well as EHR vendors' adaptability to hospitals will affect attainment of meaningful use. For example, rural hospitals may not have resources and capacity to purchase expensive EHRs capable of customizing applications to fit hospitals' practices. However, EHR vendors that are popular in rural hospitals or smaller hospitals that provide applications with lower costs may not have the capacity to make adjustments or customize their applications. In either case, rural hospitals will face challenges in attaining meaningful use. More research is needed to identify variations in EHR vendors' abilities to adapt to hospitals' contextual factors.

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