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Examining Structural Constraints and Electronic Health Record Use in Acute Care Hospitals

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Abstract: Electronic Health Record (EHR) use is expected to quickly increase in the USA. It is the hope of the federal government and many hospitals that EHR use will not only increase, but also mature from basic applications such as EHR for results viewing (ERV) to more advanced applications such as Computerized Provider Order Entry (CPOE). Today, considerable heterogeneity exists among hospitals with regard to EHR use and the movement toward advanced EHR applications. Examining this heterogeneity is useful as hospitals move toward advanced EHR. Survey data collected from 297 acute care hospitals in 47 states suggests that critical access hospitals may be slow to use EHR, even in the early stages of ERV. Conversely, major teaching hospitals appear to be early adopters, achieving advanced ERH use. These findings are key for hospital executives, Health Information Technology managers, and policymakers facing resource allocation decisions for EHR adoption.

INTRODUCTION

Healthcare spending in the U.S.A. is expected to reach $4 trillion in 2015 – roughly 20% of gross domestic product (GDP) (Borger, Smith, Truffer, Keehan, Sisko, Poisal, et al., 2006; Bourgeois, Prater and Slinkman, 2009). These cost increases have led to a "…call for increased adoption and use of health care information technology (HIT) to address structural inefficiencies and care quality issues plaguing the US health care industry (GAO, 2005)," (Trimmer, Cellucci, Wiggins and Woodhouse, 2009: p. 55). According to Katsamakas, Janamanchi, Raghupathi and Gao (2009: p. 19), "HIT has the potential to transform the healthcare industry by increasing productivity, reducing errors and costs, facilitating information sharing and improving the quality of healthcare services (Brailer, 2005)."

Growth in hospital use of HIT is on an upward trend (Bourgeois et al., 2009). This growth is primarily led by two applications; computerized provider order entry systems (CPOE), and picture archiving computer systems – or electronic health records use for results viewing (ERV) (Dorenfest, 2004). These applications (ERV and CPOE) signify a sort of *functional sophistication* (Bourgeois et al., 2009). ERV can be defined as basic electronic health record (EHR) use and CPOE can be defined as advanced (or comprehensive) EHR use (Jha, DesRoches, Campbell, Donelan, Rao, Ferris, et al., 2009). Unfortunately, the adoption and use of these EHR technologies has been less than expected (Reardon, 2009), and heterogeneous among hospital providers (McCullough, Casey, Moscovie and Burlew, 2011). In other words, while all hospitals use EHR to some degree, the levels of sophistication vary considerably (Cohen, 2005).

The heterogeneity in EHR use among hospitals may be contingent on a variety of factors present in a hospital's environmental or operational context (Helms, Moore, and Ahmadi, 2008; Spil, LeRouge, Trimmer and Wiggins, 2009). One key contingency in such an operational context might be a hospital's structural constraints such as location or type (Li, Benton and Leong, 2002). For instance, a high volume teaching hospital treating highly acuity patients may be more likely to adopt advanced EHR applications than critical access hospitals which encounter less competition and possess fewer resources (Hough, Chen and Lin, 2005; Helms et al., 2008). Given the considerable investment afoot for EHR, it would be valuable to better understand some of the adoption patterns of specific hospital types (Bourgeois et al., 2009). Understanding contingencies may "…help to smooth IT implementation in the future," (Spil et al., 2009; p. 70).

This study explores hospital adoption of EHR by examining two unique cases of structural constraints – major teaching hospitals (MTH) and critical access hospitals (CAH) (Li et al., 2002). In doing so, this study seeks to inform two key research questions facing policymakers, hospital executives, and HIT managers. First, are certain hospital types more advanced than others with respect to EHR use? And second, if so, what contingencies may be driving this heterogeneity in EHR use? This study addresses these research questions by developing hypotheses linking hospital type to basic and advanced EHR use and testing these hypotheses using survey data collected from 297 hospitals in 47 states. Results reveal that CAH are behind in their implementation of EHR at even the basic level of results viewing. MTH are more established in terms of their EHR use, outpacing mainstream facilities at even advanced levels such as computerized provider order entry.

VARIABLES AND HYPOTHESES

The contingency perspective contends that the achievement of many organizational initiatives can be linked to contextual factors (Jayaram, Ahire and Dreyfus, 2010). These contingency factors can arise in the form of structural constraints such as the location, size, and/or teaching status of the hospital that may influence operational practices and outcomes (Li et al., 2002). The way contingency factors affect a hospital's use of EHR is of interest in this study. Thus, contingency theory is used to underpin the overarching notion posited by this study that the operational context of the hospital – its structural constraint as a MTH or CAH – will influence its use of basic or advanced EHR. CAH are postulated to exhibit lower levels of EHR use, namely in the range at, or below, that of basic EHR, while MTH are theorized to exhibit higher and more advanced EHR use (CPOE). Variables are defined in table 1.

Subconstruct	Definition	Literature
Basic EHR use	the extent to which a hospital uses electronic health records for results viewing purposes (e.g., lab reports, consultant reports, etc.).	AHA, 2005; Cutler et al., 2005; Jha et al., 2009.
Advanced EHR use	the extent to which a hospital uses electronic health records for Computerized Provider Order Entry (e.g., lab tests, consultation requests, etc.).	AHA, 2005; Cutler et al., 2005; Jha et al., 2009.
Critical Access Hospital	the extent to which a hospital is 1) located in a rural area, 2) located more than 35 miles away from any other hospital (or 15 miles in mountainous terrain), 3) maintain not more than 25 inpatient beds, and 4) maintain an annual average length of stay (ALOS) of 96 hours or less.	HRSA, 2010; McCullough et al. 2011.
Major Teaching Hospital	the extent to which a hospital is affiliated with a medical school and maintains teaching and research as core to its mission.	Li et al. (2002); McDermott and Stock (2007); Jha et al. (2009).

Table 1. Variable Definitions.

Critical Access Hospitals and EHR Use

CAH are designated as such owing to their strict compliance with certain criteria. See table 1. CAH "face many challenges in health IT adoption including financial constraints, limited access to capital, inadequate infrastructure, and limited health IT workforce," (McCullough et al., 2011: p. 329). While many concur that IT will improve safety and reduce errors, barriers to implementation are many (Hartzema, Winterstein, Johns, de Leon, Bailey, McDonald, and Pannell, 2007)." For these reasons, their operational context appears to hinder CAH's adoption of EHR, even basic for results viewing. Therefore, this study postulates,

> **H1: Critical access hospitals will demonstrate lower levels of basic EHR use (Results Viewing) than non-critical access hospitals.**

Hospital IT adoption has been slow, above all with advanced IT applications such as EHR (Reardon, 2009). Often EHR use is hampered by several factors. "Lack of competition, resistance to change, and capital costs are among the major causes for healthcare's slowness to adopt IT (Hough et al., 2005)," (Helms et al., 2008: p. 81). In light of these contextual factors, it is not expected that even non-critical access hospitals will be mature in the adoption of advanced EHR. Therefore, this study postulates,

H2: Critical access hospitals will demonstrate the same levels of advanced EHR use (CPOE) as non-critical access hospitals.

Major Teaching Hospitals and EHR Use

MTH are dissimilar from non-teaching facilities in terms of their goals and mission (Li et al., 2002). These hospitals are affiliated with medical colleges, and take on extra responsibilities such as research (McDermott and Stock, 2007). Thus in this study, major teaching hospitals are defined as the extent to which a hospital is affiliated with a medical school and maintains teaching and research as core to its mission (Li et al., 2002; McDermott and Stock, 2007; Jha et al., 2009). Their involvement in research positions these facilities to be on the cutting edge best practices (McDermott and Stock, 2007). The present study builds upon the literature which suggests that MTH are more likely to adopt innovative practices, in this case centered on EHR use. Therefore, this study postulates,

H3: Major teaching hospitals will demonstrate higher levels of EHR for CPOE (advanced EHR) use than non-major teaching hospitals.

Other researchers have hypothesized differences in the practices of teaching and non-teaching hospitals and found no statistically significant differences (see Goldstein and Naor, 2005; Tucker, Nembhard and Edmondson, 2007). McFadden, Henagan and Gowen, 2009). These mixed results may be owing to the notion that MTH are only different in the most advanced practices. Mainstream hospitals follow MTH in their adoption of new practices, thereby closing the gap on what was formerly thought of as *cutting edge.* Therefore, this study postulates,

H4: Major teaching hospitals will demonstrate the same levels of EHR for Results Viewing (basic EHR) use as non-major teaching hospitals.

Comparing Critical Access Hospitals and Major Teaching Hospitals

In sum, this discussion points out key differences between CAH and MTH. Given their differing operational contexts (financial and human resources, etc.), it should be expected that MTH demonstrate a high level of EHR use at both the basic and advanced varieties. Therefore, this study postulates,

H5: Major teaching hospitals will demonstrate higher levels of EHR for Results Viewing (basic EHR) use and of EHR for CPOE (advanced EHR) use than critical access hospitals.

RESEARCH METHODS

Data collection

Survey data was collected using a cross-sectional self-administered survey of American Hospital Association (AHA) members. The sample frame consisted of 671 hospital executives from 644 acute care facilities. 312 responses were received, generating a response rate of 46.5% (312/671). After deleting responses for missing or inappropriate values and averaging duplicative responses, the analysis sample consisted of 297 hospitals. Sample characteristics are displayed in tables 2 and 3.

Characteristics	Respondents
Job title	
Director of Case Management	63 (21%)
Chief Nursing Officer	43 (15%)
Vice President of Patient Care Services	43 (15%)
Director of Nursing	21 (7%)
Director of Quality Initiatives	17 (6%)
Quality Assurance Manager	14 (5%)
Director of Patient Care Services	10 (3%)
Chief Operating Officer	7 (2%)
Unit Manager	6 (2%)
Vice President of Quality Initiatives	4 (1%)
Chief Executive Officer	2 (1%)
Vice President of Medical Affairs	1 (0%)
Vice President of Case Management	1 (0%)
Other	47 (16%)
Did not report.	22 (7%)

Note: Numbers represent frequency, followed by the percentage (rounded) of the sample in parentheses.

Table 2. Respondent characteristics (job titles).

Characteristics	Respondents
Hospital type	
Tertiary care center	66 (22%)
Community hospital	188 (63%)
Critical access hospital	34 (11%)
Other/missing values	9 (3%)
Ownership status	
For-profit hospital	39 (13%)
Non-profit hospital	222 (75%)
Public hospital	30 (10%)
Other/missing values	6 (2%)
Size – number of beds	
< 49	39 (13%)
50-99	59 (20%)
100-199	64 (22%)
200-399	76 (26%)
> 400	53 (18%)
Other/missing values	6 (2%)
Teaching status	
Major teaching hospital	59 (20%)
Minor teaching hospital	92 (31%)
Nonteaching hospital	141 (48%)
Other/missing values	5 (2%)

* Hospitals from 47 states participated in the study.
Note: Numbers represent frequency, followed by the percentage (rounded) of the sample in parentheses.

Table 3. Sample characteristics.

Finally, tests for non-response bias produced no statistically significant differences for targeted demographic variables between the respondents and non-respondents providing evidence that non-response bias is not problematic in the data (Armstrong and Overton, 1977).

DATA ANALYSIS AND RESULTS

Measures

Exploratory factor analysis (EFA) was employed to assess simple factor structure among the variables (Hair, Black, Babin, Anderson and Tatham, 2006). The items displayed in Table 4 were analyzed collectively using SPSS 15.0. This fashioned a total explained variance of 80.3%, and a Kaiser-Meyer-Olkin value of 0.79 indicating a suitable number of factors present in the model (Hair et al., 2006) to explain the EHR phenomenon under study as well as to provide evidence of sampling accuracy. Factor loadings were generated using Principle Components Analysis extraction method and Varimax rotation method with Kaiser Normalization. The number of factors was not specified in the analysis. This revealed a simple factor structure of two factors, both of which demonstrate Eigenvalues > 1. Item coefficient values were suppressed at < 0.4 values given that these are considered small (Hair et al., 2006) and not indicative of cross-loading.

All factors loadings are above 0.5, demonstrating convergent validity (Bagozzi and Yi, 1988) and all exceed 0.7 which Hair et al., (2006) considers indicative of well-defined structure. Evidence of discriminant validity is provided as none of the loadings are greater than 0.4 on more than one factor (Hair et al., 2006). Content validity was confirmed by the literature review and theory development. Cronbach's alpha was employed as a test of reliability. Both factors scored over 0.90 and are therefore acceptably reliable measures (Hair et al., (2006). See Table 5.

Measurement items	EHR for results viewing	EHR for Computerized Provider Order Entry
We use EMR to view:		
ERV2 radiology reports.	0.93	
ERV1 lab results.	0.91	
ERV4 diagnostic test results.	0.90	
ERV3 radiology images.	0.87	
ERV5 diagnostic test images.	0.81	
We use EMR to order:		0.95
CPOE2 radiology tests.		0.95
CPOE1 laboratory tests.		0.90
CPOE4 consultants reports.		0.87
CPOE3 medications.		0.82
CPOE5 nursing orders.		

Notes:
1. Extraction Method: Principal Component Analysis.
2. Rotation Method: Varimax with Kaiser Normalization.

Table 4. Operational definitions and exploratory factor loadings (factor structure).

Correlations among the variables and descriptive statistics are provided in Table 5. It should be noted that correlations exist among the variables at a $p < 0.01$ level. This is likely owing to the similarity in the wording of the questions as well as the theoretical construction of the variables both dealing with EHR use (see Table 4 for the operational definitions/items). The correlation is well below the 0.90 cutoff as a measure of collinearity suggested by (Hair *et al.*, 2006). Lastly, the variables were tested for kurtosis and skewness, neither of which were shown to be problematic.

Variable	μ	σ	Skewness	Kurtosis	α	Corr.
EHR for results viewing	4.56	0.57	-1.95	6.20	0.92	n/a
EHR for Computerized Provider Order Entry	3.57	1.06	-0.75	-0.01	0.94	0.189***

Notes:
Sample $n = 297$
Corr. = correlation between the two variables significant at *** $p < 0.01$.

Table 5. Descriptive statistics.

Hypothesis Testing

T-tests were employed to test the hypotheses theorized in this study. The t-test is a statistical procedure used to assess mean differences between groups or samples (see Hong, Dobrzykowski and Vonderembse, 2010), and have been used in similar studies of EHR (McCullough et al., 2011). Table 6 displays the results for the testing of hypotheses 1 and 2 with regard to CAH.

Variables and means	Basic EHR use (ERV)	Advanced EHR use (CPOE)
Critical access hospitals ($n = 34$)	4.36	3.30
Non-critical access hospitals ($n = 263$)	4.58	3.61
t-value	2.20**	$1.77^{n/s}$

**Significant at $p < 0.05$. Scale anchors: 1 = strongly disagree, 5 = strongly agree.

Table 6. T-tests for critical access hospitals.

Hypothesis 1, *critical access hospitals will demonstrate lower levels of basic EHR use (Results Viewing) than non-critical access hospitals,* is supported as CAH (μ=4.36) are statistically different (lower) than non-critical access hospitals (μ=4.58) at the $p < 0.05$ level (t=2.20) in terms of their use of basic EHR. Hypothesis 2, *critical access hospitals will demonstrate the same levels of advanced EHR use (CPOE) as non-critical access hospitals* is also supported as CAH (μ=3.30) are not statistically different from non-critical access hospitals (μ=3.61) in terms of their use of advance EHR.

Table 7 displays the results for the testing of hypotheses 3 and 4 with regard to MTH. Hypothesis 3, *major teaching hospitals will demonstrate higher levels of EHR for CPOE (advanced EHR) use than non-major teaching hospitals,* is supported as MTH (μ=3.89) are statistically different (higher) than non-critical access hospitals (μ=3.49) at the $p < 0.01$ level (t=3.04) in terms of their use of advanced EHR. Hypothesis 4, *major teaching hospitals will demonstrate the same levels of EHR for Results Viewing (basic EHR) use than non-major teaching hospitals,* is also supported as MTH (μ=4.60) are not statistically different from non-major teaching hospitals (μ=4.55).

Variables and means	**Basic EHR use (ERV)**	**Advanced EHR use (CPOE)**
Major teaching hospitals (*n* = 59)	4.60	3.89
Non-major teaching hospitals (*n* = 238)	4.55	3.49
t-value	0.57 $^{n/s}$	3.04***

***Significant at p < 0.01; ** p < 0.05. Scale anchors: 1 = strongly disagree, 5 = strongly agree.

Table 7. T-tests for major teaching hospitals.

Table 8 displays the results for the testing of hypothesis 5 which examines differences between CAH and MTH. Hypothesis 5, *major teaching hospitals will demonstrate higher levels of EHR for Results Viewing (basic EHR) use and of EHR for CPOE (advanced EHR) use than critical access hospitals,* is supported as MTH (μ=4.60) are statistically different (higher) than non-critical access hospitals (μ=4.36) at the $p < 0.05$ level (t=2.03) in terms of their use of basic EHR as well as in terms of their use of advanced EHR in which case MTH's μ=3.89, while CAH's μ=3.30 (statistically significant at $p < 0.01$; t=3.11).

Variables and means	**Basic EHR use (ERV)**	**Advanced EHR use (CPOE)**
Critical access hospitals (*n* = 34)	4.36	3.30
Major teaching hospitals (*n* = 59)	4.60	3.89
t-value	2.03**	3.11***

***Significant at p < 0.01; ** p < 0.05. Scale anchors: 1 = strongly disagree, 5 = strongly agree.

Table 8. T-tests comparing critical access and major teaching hospitals.

DISCUSSION AND CONCLUSIONS

Hospitals in the U.S.A. are under tremendous pressure to implement EHR (McCullough et al., 2011) and as a result substantial investment in HIT is underway (Bourgeois et al., 2009). The movement toward better integration and improved collaboration anticipated to result from EHR is an important goal for even the smallest rural hospitals (HRSA, 2010). Unfortunately, EHR use is not universally achieved among hospitals. This study examines differences in EHR use among acute care hospitals in the U.S.A. in an attempt to provide a much needed understanding of current trends and provide direction for improvement (Spil et al., 2009). As such, this study produces valuable finds for practitioners and scholars alike.

For practitioners, data from 297 acute care hospitals from 47 states reveals that hospital EHR implementation is indeed heterogeneous. Critical access hospitals appear to be lagging behind the curve in terms of their adoption of even basic EHR. Conversely, major teaching hospitals are leading the way demonstrating high levels of basic as well as advanced EHR use when compared to critical access hospitals. These findings inform the first research question under study, *are certain hospital types more advanced than others with respect to EHR use?* This is a key finding as this study provides empirical evidence illustrating the heterogeneity in EHR adoption, and in doing so, uncovers EHR trends among specific hospital types based on a hospital's context or structural constraints (Li et al., 2002). Through literature review, this study informs the second research question, *what contingencies may be driving this heterogeneity in EHR use?* Following the establishment of heterogeneity between critical access hospitals and major teaching hospitals, the key characteristics of their operating contexts emerge as important contingency factors in their implementation of EHR. For example, these findings should draw attention to the observations made by McCullough et al. (2011) and Helms et al. (2008) who suggested that critical access hospital suffer from limited access to capital, financial constraints, inadequate infrastructure, and limited health IT workforce. It follows that while major teaching hospitals may appear to have greater need for, and ability to achieve the integration realized by EHR owing to their contingency factors of high levels of patient acuity, operating complexity, and substantial resources (Li et al., 2002), true system integration can only be achieve when all healthcare providers use EHR. As such, additional resources (financial as well as human) would be well served to be dedicated for EHR implementations in critical access hospitals.

This study makes two primary contributions for scholars. First, it provides a rare theoretically grounded examination of EHR use. Contingency theory (see Jayaram et al., 2010) is shown to be an effective theoretical lens for understanding the motivations of certain hospitals to implement specific types or EHR while others do not. In this way, contingency theory may help scholars to better explore EHR trends, an important undertaking in the effort to smooth future implementations (Spil et al., 2009). This lens was also key in the development of the findings put forth for practitioners. Second, this study employed a rare multi-item approach to measuring EHR. This is a valuable approach in providing a rich measure of both EHR for results viewing, framed as basic EHR, and EHR for computerized provider order entry, framed as advanced EHR. These measures have been shown to be both highly valid and reliable. Previous studies have analyzed individual measurement items while ignoring the phenomenon as an aggregate psychometric measure (see McCullough et al., 2011).

LIMITATIONS AND FUTURE RESEARCH

While this study does contribute to the scholarly and practical understanding of EHR use, it is plagued by certain limitations. First, the limitations consistent with survey research (i.e., challenges related to respondent bias and measurement of perceptions) are possible owing to the single respondent data collection method employed by this study. Second, the focus of this study was on the contingency factors or structural constraints that may influence EHR use. Certainly, other factors may influence EHR use that were not included in this study, and are worthy of future investigation. Finally, while important insights are provided into the differences between critical access hospitals and major teaching hospitals in terms of their EHR use, this represents but a small fraction of the potential learnings. Clearly more work is needed to explore phenomena related to EHR as encouraged by Spil et al. (2009: p. 70) who pointed out the need for "…continuous learning, evaluation, and understanding in both practice and research."

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