Can HIT Work Alone? A Security and Socio-Economic Perspective of Healthcare Quality

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Abstract
Healthcare delivery system can immensely benefit from the use of HIT (Healthcare Information Technology). Clinical and administrative automation in hospitals can improve clinical quality through reduced mortality. Previous literature has failed to identify the impact of security technology usage and socio-economic factors on clinical quality improvement. Our paper addresses this gap through the security-HIT interaction and socio-economic impact on overall clinical quality. We used OLS based regression technique to validate our model. We combined survey data of U.S. hospitals from Dorenfest Institute and Centers for Medicare & Medicaid Services from 2011 to 2013. Results from our study will guide healthcare professionals to understand the interaction effect of security, effective technology integration in clinical and administrative automation systems. We also strong evidence of socio-economic impact on mortality rate reduction.

Keywords
Healthcare IT, Clinical Quality, Security, Moderator, Socio-Economic Factors

Introduction
The expected growth rate of the prime Healthcare IT (HIT) markets of USA and Europe is 11.80%, between 2014 to 2020. Asia-Pacific, Latin America, and the Middle East are also catching up rapidly in HIT (Digital Journal 2016). In the third quarter of 2015, forty-nine companies raised a capital of $689 million for HIT projects globally (MobiHealth, 2015).

HIT adoption will facilitate a proper healthcare delivery system. It comprises of players such as patient, physician, nurses, administrators, insurers and regulators (Fichman et al. 2011). HIT applications improve patient outcomes, prevent unwarranted surgical procedures, reduce medical errors and cost reductions for the hospitals as well as the patients (Bowens et al. 2010). Use of uniform standard procedures and data entry techniques help in good quality health information retrieval (Morahan-Martin et al. 2004). However, improper HIT adoption may lead to fatal consequences (Classen et al. 1997, Verhoeven et al. 2010). HIT adoption is dependent on people-process-technology and external environment (Agarwal et al. 2010). Security and privacy concerns are the prime causes for slow adoption of HIT (Chaudhry et al. 2007).

Use of HIT, enhances the chances of patient health information (PHI) being breached and confidentiality-integrity-authenticity (CIA) might get compromised. In 2014, a cross-site scripting flaw in the myGov website in Australia had the potential to expose any myGov user's account information (The Sydney Morning Herald, 2014). Data security threat is a primary deterrent against the digital progress of National Health Service (The Guardian, 2014). The fear of data breach by insurers and employers from employee's wearable devices resulted in sparse adoption and usage of such devices (The Guardian, 2015).

In this paper, we model the impact of HIT on healthcare delivery system, using *Mortality Rate (heart attack, heart failure, pneumonia)* as the key performance indicator. Mortality rate is a proxy for clinical quality (CQual). HIT for this study includes both clinical and administrative processes. We also study the impact of security, as a moderating variable, and socio-economic factors (such as literacy, per capita income and income disparity), on CQual.

Literature Review

Existing literature on HIT have been categorized into HIT adoption and HIT impact by Agarwal et al. (2010). HIT design and implementation, quantifying the payoff in terms of quality and cost, workflow integration are the other areas of research. Black et al. (2011) identified that there is a large gap between the postulated and the empirical outcomes. Chaudhry et al. (2006) also explained the reduction of the effect of clinical automation systems (CAS) in case of large-scale analysis of hospitals. All these challenges towards measuring the impact of automation on CQual made it necessary to understand and explore more factors affecting CQual measurements. In this paper, we tried to quantify the impact of HIT on CQual while accounting for socio-economic factors and security as part of HIT success.

Several authors dedicated much of their effort to understand the adoption of information systems in healthcare. Technology Acceptance Models (TAM, TAM2) and Unified Theory of Acceptance and Use of Technology (UTAUT) have been used extensively to understand the adoption of electronic medical records, and other clinical automation (Liu & Ma 2006; Holden & Karsh 2010). However, the need for extraneous variables for better understanding of the model restricted such studies (Holden & Karsh 2010). Connel & Young (2007) designed a framework that suggested a move from administrative (admin) to clinical automation for marked improvement. Further, there were frameworks and models related to security and privacy concerns of sensitive patient information within the internal workflow. For example, role-based delegation framework (Zhang et al. 2002) or creating conflict sets for multi-task assignment (Bai et al. 2014), both of which discussed access control and user authentication as a part of security measures. Parks et al. (2011) mentioned prior notice to the patient about any information disclosure are ways forward towards fair information practices. One important factor that we have included in our paper is security which is an essential inclusion in our HIT impact model owing to the concerns related to data access control.

On the other hand, Devraj and Kohli (2003) found that HIT usage helps in improving hospital revenue and quality (measured using mortality rates) while using the age of hospital, patient income, outpatients and number of employees as controls. However, there has been literature that discussed the limited impact of HIT on clinical quality and expenses (Agarwal et al. 2010; Black et al. 2011; Himmeslstein et al. 2010). However, Bardhan and Thouin (2013) did a statistical study of HIT impact on process care quality as well as operating expenses. They used Dorenfest and CMS databases where they explained that clinical and scheduling systems do result in higher "Total Quality."

In this paper we used clinical and admin automation systems (CAS and AAS) as shown in Bardhan and Thouin 2013, for understanding the level of automation in a hospital. However, we strengthened our model by including clinical and admin application categories instead of individual applications to obtain a complete view of the level of automation. We also included security measures and socio-economic factors to understand their impact on overall CQual.

Theory Foundation

Research related to resource-based view theory explains competitive advantage lies in the valuable tangible and intangible assets of the firm (Wernerfelt et al. 1984). Even if a resource can be useful in supporting a "resource position barrier", it is not a sufficient reason for a firm to be interested in it. Hence, it directs us to measure the impact of HIT through operational efficiency that has effect on the overall CQual. However to optimize the effect of IT, available tangible resources like bed count, physician count and security, and intangible resources like socio-economic factors and hospital type, play a vital role. Low IT productivity in healthcare led us to look into the theory of IT productivity paradox (Brynjolfsson 1993) which is a result of mismeasurement of input and output, lags due to learning and adjustment, mismanagement of IT and redistribution of profits. Our study tries to reduce the gap of mismeasurement in input and measures the output in terms of operational efficiency that is reflected by CQual.

Model and Hypothesis Formation

In this section we formulate three linear equations to determine negative mortality rates for each medical condition, that is, heart attack (HA), heart failure (HF) and pneumonia (PN) in equations (1), (2) and (3) as shown below. The factors shown in Figure 1 are used in the equations.

$$(HeartAttack\_MortalityRate) = \alpha_0 + \alpha_1 * NofBeds\ (Hospital\ Size) + \alpha_2 * Physician\_Total + \alpha_3 * AntiVirus\_Count + \alpha_4 * IDS\_Count + \alpha_5 * UA\_Count + \alpha_6 * Government + \alpha_7 * Voluntary + \alpha_8 * Proprietary + \alpha_9 * Academic + \alpha_{10} * Critical\_Special + \alpha_{11} * General + \alpha_{12} * Literacy + \alpha_{13} * IncDis + \alpha_{14} * PCI + \alpha_{15} * Clinical\_Proportion + \alpha_{16} * Admin\_Proportion + \alpha_{17} * Moderator\_1 + \alpha_{18} * Moderator\_2 + \alpha_{19} * Moderator\_3 + \alpha_{20} * Moderator\_4 + \alpha_{21} * Moderator\_5 + \alpha_{22} * Moderator\_6 \text{ -------------}(1)$$

$$(HeartFailure\_MortalityRate) = \beta_0 + \beta_1 * NofBeds\ (Hospital\ Size) + \beta_2 * Physician\_Total + \beta_3 * AntiVirus\_Count + \beta_4 * IDS\_Count + \beta_5 * UA\_Count + \beta_6 * Government + \beta_7 * Voluntary + \beta_8 * Proprietary + \beta_9 * Academic + \beta_{10} * Critical\_Special + \beta_{11} * General + \beta_{12} * Literacy + \beta_{13} * IncDis + \beta_{14} * PCI + \beta_{15} * Clinical\_Proportion + \beta_{16} * Admin\_Proportion + \beta_{17} * Moderator\_1 + \beta_{18} * Moderator\_2 + \beta_{19} * Moderator\_3 + \beta_{20} * Moderator\_4 + \beta_{21} * Moderator\_5 + \beta_{22} * Moderator\_6 \text{ -----------}(2)$$

$$(Pneumonia\_MortalityRate) = \Upsilon_0 + \Upsilon_1 * NofBeds\ (Hospital\ Size) + \Upsilon_2 * Physician\_Total + \Upsilon_3 * AntiVirus\_Count + \Upsilon_4 * IDS\_Count + \Upsilon_5 * UA\_Count + \Upsilon_6 * Government + \Upsilon_7 * Voluntary + \Upsilon_8 * Proprietary + \Upsilon_9 * Academic + \Upsilon_{10} * Critical\_Special + \Upsilon_{11} * General + \Upsilon_{12} * Literacy + \Upsilon_{13} * IncDis + \Upsilon_{14} * PCI + \Upsilon_{15} * Clinical\_Proportion + \Upsilon_{16} * Admin\_Proportion + \Upsilon_{17} * Moderator\_1 + \Upsilon_{18} * Moderator\_2 + \Upsilon_{19} * Moderator\_3 + \Upsilon_{20} * Moderator\_4 + \Upsilon_{21} * Moderator\_5 + \Upsilon_{22} * Moderator\_6 \text{ -----------}(3)$$

where Moderator_1 = AntiVirus_Count * Clinical_Proportion
Moderator_2 = AntiVirus_Count * Admin_Proportion
Moderator_3 = IDS_Count * Clinical_Proportion
Moderator_4 = IDS_Count * Admin_Proportion
Moderator_5 = UA_Count * Clinical_Proportion
Moderator_6 = UA_Count * Admin_Proportion

HIT Applications

Improving healthcare delivery system using CAS and AAS in healthcare improves CQual (Bowens et al. 2010). Health information systems (HIS) improves healthcare delivery system and results in patient satisfaction (Nahm et al. 1999; Kazley et al. 2012). *Table 1* shows the different HIS used in our analysis.

Clinical IT systems categories	Admin IT systems categories
• Cardiology & PACS • ED/Operating Room/Respiratory/ Clinical Systems • Electronic Medical Record • Laboratory • Nursing • Pharmacy • Radiology & PACS	• Human Resources • Document/Forms Management • Financial Decision Support • General Financials • Health Information Management (HIM) • Revenue Cycle Management • Supply Chain Management • Transcription

Table 1: HIT Application categories for medical and non-medical automation in hospitals

Hypothesis 1 (H1): Clinical information system has a negative effect on mortality rates.
Hypothesis 2 (H2): Admin information system has a negative effect on mortality rates.

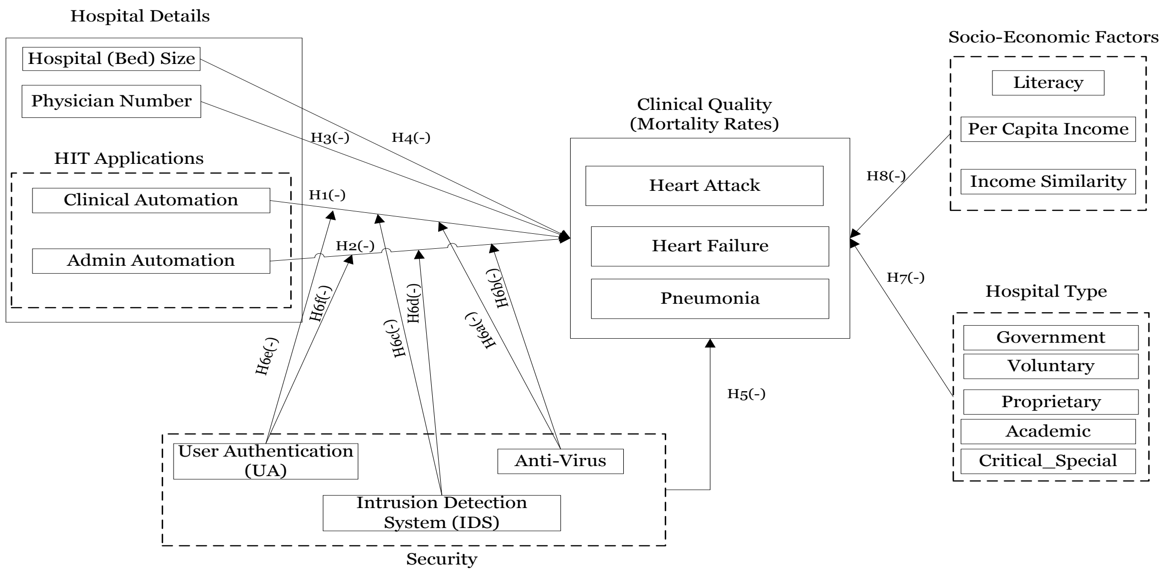

Figure 1: Model to demonstrate Mortality Rate Factors

Physician Count

The number of physicians has a positive effect on patient satisfaction (Gok et al. 2013). Patient satisfaction is the outcome of high-quality care provided by healthcare providers (Beattie et al. 2002; Laschinger et al. 2005). Thus, increase in the number of physicians results in high care quality and reduced mortality rates.

Hypothesis 3 (H3): Physician count negatively affects mortality rates.

Hospital Size

Hospital size is measured by the number of beds. Hospital size affects framing of regulatory compliance (D' Aunno et al. 2000) and hospital performance (Shohet et al. 2004, Palvia et al 2012, Bardhan and Thouin 2013). However, workflow automation through EHR system does not provide many benefits when the size of the hospital increases (Thakkar et al. 2006).

Hypothesis 4 (H4): Number of beds in a hospital has a negative effect on mortality rates.

Security Software:

Privacy and security breach causes harassment and discrimination for the patient and an economic loss to the providers and employers (Ohno-Machado et al. 2004; Neubauer et al. 2011). It includes unwanted modification or deletion of existing health records, causing deterioration in the CQual of the hospital.

Hypothesis 5 (H5): Security has a negative effect on mortality rates.

Security as a Moderator

Apart from the effect of security on mortality rates, we are also interested in understanding the effect of security installation for HIT applications on mortality rates. For this purpose, we included moderator variables that capture the interaction between standardized values of security measures with CAS and AAS applications.

Hypothesis 6 (H6): Security, as a moderator for information systems, moderates and enhances its negative effect on mortality rates.
H6a: Anti-virus (AV) moderates and enhances the negative effect of CAS on mortality rates.

H6b: Anti-virus (AV) moderates and enhances the negative effect of AAS on mortality rates.
H6c: Intrusion detection system (IDS) moderates and enhances negative effect of CAS on mortality rates.
H6d: Intrusion detection system (IDS moderates and enhances negative effect of AAS on mortality rates.
H6e: User Authentication (UA), moderates and enhances the negative effect of CAS on mortality rates.
H6f: User Authentication (UA), moderates and enhances the negative effect of AAS on mortality rates.

Hospital Type

Hospital type is important because the physicians at public hospitals have higher self-efficacy, that is, belief in their capability to safeguard and protect patient"s information privacy, compared to their counterparts in private healthcare facilities (Warkentin et al. 2006). On an average, administrative staff exhibit higher self-efficacy than medical staff across both public and private hospitals. (Appari et al. 2009). Thus, organizational culture and hospital type are important in influencing the quality of care of hospital (Palvia et al. 2012). Bardhan and Thouin (2013) also observed that the non-profit voluntary and the non-teaching hospitals are much more compliant to process quality than profit-making or teaching hospitals.

Hypothesis 7 (H7): Hospital type, especially, voluntary and non-academic hospitals, have a negative effect on mortality rates.

Social-Economic Factors

We have also considered socio-economic factors such as literacy, causing digital divide (Bodie and Dutta 2008), per capita income affecting technology diffusion (Slade et al. 2001), and income disparity (Blendon et al. 2002) to account for successful implementation and adoption of HIT. However, supporting technology diffusion and adoption does not ensure interaction of socio-economic factors. Hence, we directly measured the impact of social factors as a source of the improvement in care quality.

Hypothesis 8 (H8): Socio-economic factors have a negative effect on mortality rates.

Data

We obtained the research data from three different data sources on U.S. hospital such as Dorenfest Institute for Health Information (HIMSS) (HIMSS 2004), Hospital Compare Website maintained by the Centers for Medicare & Medicaid Services (CMS) and America's Health Rankings (AHR) published by United Health Foundation. *Table 2* explains the details about each of the variables and the databases affiliations. We matched the provider number of CMS data with the Medicare number of Dorenfest data and thus tried to match the hospital data of CMS and Dorenfest. The HAEntityId is different for the different branches of the same hospital while the Medicare number remains the same. Further, we filtered the data to take up only those hospitals for which we had data for all the three years from 2011 – 2013 and the compact dataset consists of 966 hospitals. Our data consists of mortality rates for heart attack (HA) and heart failure (HF) as heart diseases account for 25% of total deaths in United States. We need to keep in mind that HF is more critical than HA in terms of mortality. Moreover, we also looked into pneumonia mortality rates (2.3% of total death) which has low to moderate death rate (Heron 2012). Thus we believe that our study is valid for overall healthcare delivery system.

We observe that each security count has strong correlation with CAS and AAS but limited significance with mortality rates. Hereafter, we will be using the abbreviations of each variables (as shown in Table 2) in the results and discussion section.

Methodology

We checked the variables in the hypothesis empirically using hospital level data; first, checking for the correlation table, and then we use stepwise Ordinary Least Squares (OLS) Regression analysis to identify the final set of variables that affect the respective mortality rates. The different steps that we performed in the process of obtaining the results are summarized below in five simple steps.

Step 1: *Merging of Data from Dorenfest, CMS and AHR for the years 2011 to 2013.*
Step 2: *Data Transformation:*
i) Transforming Security, Hospital Type into binary dummy variables.

ii) Transforming State to obtain Literacy rate, Per Capita Income and Income Similarity rate.
Iii) Calculation of CAS and AAS scores are as follows:

$$\text{CAS}= \frac{\text{Number of Automated Clinical Systems}}{\text{Total Number of Clinical Systems}} \text{ X } 100$$

$$\text{AAS} = \frac{\text{Number of Financial,Scheduling,and HR Systems}}{\text{Total Number of Financial,Scheduling,and HR Systems}} \text{ X } 100$$

Step 3: *Run bivariate correlation for the variables in Table 2.*
Step 4: *Moderator Formation:*
i) We further used standardized values for all the three security measures, CAS, and AAS.
ii) Multiply each security measure with CAS and AAS to obtain six moderators.
Step 5: *Run stepwise OLS regression for each HA, HF, and PN mortality rates separately including the moderators obtained in Step 5. For each regression, use only those variables from that show correlation for each of the Y variables.*

Abbreviation	Variables	Mean	Std. Dev.	N	Description	Data Source
X1	NofBeds	259.39	211.677	2898	Number of beds	HIMSS
X2	Physician_Total	447.87	434.063	1706	Physician Count	HIMSS
X3	AntiVirus_Count	.69	.461	2898	AV Count	HIMSS
X4	IDS_Count	.90	.296	2898	IDS Count	HIMSS
X5	UA_Count	.53	.499	2898	UA Count	HIMSS
X6	Government	.17	.378	2898	Government hospitals	CMS
X7	Voluntary	.69	.464	2898	Voluntary hospitals	CMS
X8	Proprietary	0.00	0.00	2898	Profit making hospitals	CMS
X9	Academic	.07	.250	2898	Academic hospitals	HIMSS
X10	Critical_Special	.09	.283	2898	Critical hospitals	HIMSS
X11	General	.85	.362	2898	General hospitals	HIMSS
X12	Literacy	76.80	6.41	2898	Literacy Rate	AHR
X13	IncDis	.46	.018	2898	Income Similarity Rate	AHR
X14	PCI	41.36	5.86	2898	Per Capita Income	AHR
X15	Clinical_Proportion	54.05	21.312	2898	CAS	HIMSS
X16	Admin_Proportion	77.03	16.17	2898	AAS	HIMSS
Y1	HeartAttack_MortalityRate	15.21	1.50	2378	HA Mortality	CMS
Y2	HeartFailure_MortalityRate	11.70	1.61	2776	HF Mortality	CMS
Y3	Pneumonia_MortalityRate	11.87	1.79	2847	PN Mortality	CMS

Table 2: Descriptive statistics of the variables used in the final dataset.

Results and Analysis

Table 3 shows the correlation between the variables used in Equations (1), (2) and (3). We further analyze the results for each of the mortality rates for a better understanding of the predictive model.

Heart Attack Mortality Rate

As shown in Table 3, H3 and H4 are confirmed. AV (X3) and UA (X5) shows negative correlation (H5 has 66.66% conformance), implying that access control (Bai et al. 2014, Zhang et al. 2002) and securing of applications by anti-virus improve care quality. Voluntary non-profit (X7), academic (X9) and critical-care hospitals (X10) have reduced HA mortality rate (Y1) than general (X11) or government (X6) hospitals, unlike what has been observed by Bardhan and Thouin (2013) for 2004-2006 data. This improvement might be due to proactive and efficient adoption of HIT and improved collaboration among academic and voluntary hospitals through telemedicine and EHR. Correlation results of literacy (X12), per capita income (X14), clinical applications (X15) and admin applications (X16) conform to the given hypothesis.

In Table 4, we observe positive coefficient for X10, which means that there is some marginal effect of other factors. For example X7, which has a significant negative coefficient to mortality, is also negatively correlated with X10. The low positive coefficient for moderator_5 reiterates the fact that adapting new technology and security in practice, might be difficult (Chaudhry et al. 2006). This is caused by general lag in training and awareness (Brynjolfsson 1993), rudimentary security measures and viewing security as a cost for doing business.

	X1	X2	X3	X4	X5	X6	X7	X9	X10	X11	X12	X13	X14	X15	X16	Y1	Y2	Y3
X1	1																	
X2	.318**	1																
X3	.128**	.231**	1															
X4	.034	.033	-.183**	1														
X5	.161**	.260**	.633**	-.022	1													
X6	.015	-.007	.062**	-.044*	.054**	1												
X7	.054**	.162**	.048**	-.013	.007	-.678**	1											
X9	.395**	.135**	.067**	.032	.060**	.104**	-.064**	1										
X10	-.323**	-.211**	-.001	-.104**	-.041*	.049**	.030	-.083**	1									
X11	-.019	.072**	-.044*	.059**	-.008	-.110**	.020	-.626**	-.724**	1								
X12	-.045*	.184**	.044*	-.073**	.053**	-.165**	.216**	.062**	.135**	-.148**	1							
X13	.149**	-.002	.070**	.018	.071**	.071**	-.132**	.015	-.199**	.145**	-.477**	1						
X14	.093**	.174**	.074**	-.028	.080**	-.131**	.161**	.051**	-.081**	.028	.357**	.315**	1					
X15	.332**	.995**	.239**	.034	.266**	-.007	.170**	.141**	-.220**	.075**	.173**	-.021	.151**	1				
X16	.249**	.599**	.229**	.053**	.294**	-.050**	.156**	.121**	-.146**	.031	.026	-.030	.025	.631**	1			
Y1	-.207**	-.138**	-.044*	.016	-.051*	.101**	-.147**	-.090**	-.027	.095**	-.073**	.005	-.112**	-.136**	-.099**	1		
Y2	-.186**	-.001	-.016	.051**	-.013	.014	.000	-.096**	.005	.067**	-.006	-.129**	-.131**	-.006	-.039*	.248**	1	
Y3	-.166**	-.105**	-.078**	.012	-.070**	.089**	-.113**	-.080**	.079**	-.005	-.067**	-.014	-.119**	-.107**	-.143**	.323**	.415**	1
**. Correlation is significant at the 0.01 level (2-tailed).																		
*. Correlation is significant at the 0.05 level (2-tailed).																		

Table 3: Correlation table of Variables

	HA		**HF**		**PN**	
	α	**Sig.**	**β**	**Sig.**	**ϒ**	**Sig.**
(Constant)		.000		.000		.000
X1	-.118	.001	-.144	.000	-	-
X2	-.196	.000	-.098	.004	-.211	.000
X4	-	-	.054	.026	-	-
X7	-.122	.000	-	-	-.054	.028
X9	.074	.009	.075	.045		
X10	-	-	-	-	.083	.001
X11	-	-	.072	.038	-	-
X12	-.051	.064	-	-	-.068	.009
X13	-	-	-.075	.003	-	-
X14	-.074	.007	-.073	.004	-.043	.098
X16	-	-	-	-	-.055	.025
moderator_1	-	-	.056	.022	-	-
moderator_3	-	-	.086	.000	-	-
moderator_5	.067	.007	-	-	.092	.000
Adjusted R^2	0.111		0.069		0.0898	

Table 4: Regression Analysis of Mortality Rates

Heart Failure Mortality Rate

In Table 3, IDS (X4) shows positive correlation with Y2 (HF mortality) which reiterates the lack of training and awareness. Income similarity rate (X13) negatively impacts Y2 and CQual. Insignificant correlation of CAS and AAS can be due to the criticality of HF condition. The correlation between Y2 and X1, X2, X9, X14 and X16 are similar to Y1.

Regression results in Table 4 show that moderator_1 (Anti-Virus X Clinical Application) and moderator_3 (IDS X Clinical Application) have low positive coefficients indicating insignificant effect on HF mortality (Chaudhry et al. 2006, Brynjolfsson 1993). X4 and X13 plays a role in the Y2 model in increasing and decreasing the mortality rate respectively. Other contributors to the Y2 regression model are X1, X2, X9, X11 and X14 of which X9 and X11 negatively affects CQual and hence increases HF mortality.

Pneumonia Mortality Rate

From the table, we observe Y3 has correlation results similar to that of Y1. The variables X1, X2, X3, X5, X12, X14, X15 and X16 have significant negative correlations with Y3. Based on hospital type variables, X6 and X10 has significant positive correlation with Y3 which shows that pneumonia treatment quality is much better in voluntary or academic hospitals.

Table 4 illustrates negative significance for physician number, voluntary hospitals, literacy, per capita income and moderator_5 has similar coefficient polarity as observed in HA mortality rate regression model. X16 contributes to this model unlike any of the previous models, which reiterates the positive effect of HIT applications on care quality (Black et al. 2011; Himmeslstein et al. 2010).

Hypothesis		Correlation		Model Significance		
	HA	HF	PN	HA	HF	PN
H1	Y	N	Y	N	N	N
H2	Y	Y	Y	N	N	Y
H3	Y	Y	Y	Y	Y	Y
H4	Y	Y	Y	Y	Y	N
H5	P	NP	P	N	N	N
H6a	-	-	-	N	N	N
H6b	-	-	-	N	N	N
H6c	-	-	-	N	N	N
H6d	-	-	-	N	N	N
H6e	-	-	-	N	N	N
H6f	-	-	-	N	N	N
H7	NP	NP	NP	Y	P	P
H8	P	P	P	P	P	P

Table 5: Summarization of hypothesis acceptance and model acceptance

Conclusion and Road Ahead

Table 5 explains the overall success of the hypothesis formation. Acceptance (Y) is for (100 percent) conformance with the hypothesis while rejection (N) is for 0 percent conformance. Partly accepted (P) refers to 66 percent conformance while partly rejected (NP) refers to 33 percent conformance to hypotheses.

The regression result is contrary to some of our hypotheses regarding the enhancing effect of security in the performance of HIT to affect clinical quality. Moreover, the high positive correlation of the security measures with HIT shows that hospitals are keen to provide security while providing HIT. Thus, we can argue that the success of such effort depends on whether it is a proactive or a reactive one (Kwon et al. 2014). Excess time consumption by security efforts or difficulty in adaptation cannot help faster and efficient treatment. We also obtained expected the result of the negative impact of literacy rate, per capita income and income similarity rate on each of the mortality rates. Hence, we learnt that under present situation, HIT and security alone cannot improve quality unless it is well-integrated with the workflow. The managerial contribution includes the understanding of the effect of socio-economic factors, security in mortality prediction. Theoretically our research encourages us to learn the interaction between HIT and other significant factors like socio-economic issues or financial constraint. The inclusion of legal aspect of

EHR (Appari et al. 2009) can be an important factor towards ensuring compliance, and can gain importance in future studies. In future, use of fixed time effects can improve the prediction model.

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