HEALTHCARE ANALYTICS ADOPTION-DECISION MODEL: A CASE STUDY

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Abstract

Healthcare organizations (HCO) are under pressure to adopt emerging solutions with a view to improving the quality and efficiency of their operations, patient care and clinical decisions. In the literature, while recommendations have been put forth to follow an organizational approach to the adoption and implementation of analytics, there is a paucity of research into what specifically constitutes healthcare-analytics (HA), as well the antecedents that can explain and predict its adoption-decisions. In this paper, we fill this gap, by first proposing a typology for HA and an adoption-decision model that integrates the TOE framework with DeLone and McLean IS Success Model. We use a case study for the initial validation of the typology and the model. Our study reveals that the HCO studied has the same types of the data proposed in our typology, although the usage of the data and current/future adoption of analytics depends on many factors beyond simply technology.

Keywords*: Healthcare Analytics; TOE framework; DeLone & McLean IS Success Model; Decision; Adoption; Case study*

1 INTRODUCTION

Healthcare industries across the world are under a huge pressure to improve their healthcare processes. In the US, though the growth rate of national health spending has been slowing down in recent past, the health expenses as a percentage of GDP have been steadily increasing from 12% to 18% (Martin et al. 2014) One way to mitigate this issue is through the leveraging of healthcare information systems in general (Raghupathi & Tan 2008) and healthcare analytics (HA) in particular. Analytics has the potential to offer solutions for improving the quality of care, cost efficiencies and operational management by driving fact-based decision making for planning, management, measurement and learning (Prewitt 2012). The analytics capability can drive improved decision capability supported by extensive use descriptive, predictive and prescriptive models (Cortada et al. 2010; Davenport & Harris 2007). While adoption of HA provides a number of opportunities for the healthcare organizations (HCOs) to innovate their business processes and services, it also comes with a set of unique challenges. First, an average hospital is projected to produce more than 665 terabytes of data with 80% of it being unstructured data (Pogorelc 2013); further, there is huge variety in the type of the collected data (Frost & Sullivan 2011). These points raise issues pertaining to data availability and data quality (Poston et al. 2006). Another issue is the lower adoption rate of EMR (Electronic Medical Records), despite the push by governments concerning record keeping, compliance & regulatory requirements, and patient care (Adler-Milstein & Jha 2014; Buntin et al. 2010; Raghupathi 2010). Finally, there are some mixed views on value creation by IT in healthcare (Sherer 2014), with some core issues being improving healthcare quality through IT, change management, privacy, security, accuracy of electronic records and decision support applications (Palvia et al. 2012). Hence it is critical for the HCOs to be very clear on the core business problem they would like to address and the role of the information technology in solving that problem.

According to Rouse & Cortese (2010), the architecture for health care service delivery typically involves four levels – clinical practices, delivery operations, system structure and healthcare eco-system. All these level are interdependent with the efficiencies that could be achieved at one level limited by the nature and efficiencies of the next level. Each health care facility is organised differently and varies from government establishment to private establishment, multi-speciality facilities to general hospital facilities, functionally organised to regionally organised to provide health care facilities. Further these organisational arrangements vary from country to country and influenced by the cultural and economic conditions and funding models. Therefore, analysing the applicability of analytics solutions to the level of the healthcare architecture in healthcare organizations requires further classification of the problem areas/domains these analytics solutions could potentially serve. As an initial step toward this goal, we propose a typology of HA applications, and validate it by using the case of a hospital in India.

Sherer (2014) calls for active participation by IS researchers to create theories for adoption of IT in healthcare, and further advocates theory-based design-science research for helping with adoption-decisions. Towards this objective, we also propose a model to explore the antecedents of HA adoption-decisions. Our model is rooted in the Technology-Organization-Environment (TOE) framework (Tornatzky et al. 1990) and brings-in elements from the DeLone and Mclean IS Success model (D&M Model) (DeLone & Mclean 2002, 2003) to address quality aspects that are important to the success of analytics. Further, we use case study methodology to test the model.

In section 2, we carry out the literature review on IT adoption models for HA; In section 3, we propose a typology of HA applications and also a model to explore the antecedents of HA adoption-decisions; In section 4, we briefly explain the case study methodology employed for the validation of the model; In section 5, we discuss the initial results of our case study; In section 6 we highlight the implications and our contributions through this research and conclude in section 7.

2 LITERATURE REVIEW ON ADOPTION MODELS

2.1 Adoption Literature

Organizations adopt information technologies with a rational expectation of creation of business value (Au & Kauffman 2003). Au & Kauffman also point out that when it comes to adoption of new innovations and emerging technologies (like HA), it requires the decision makers assess the value of IT amidst uncertainties that are sometimes very large. Therefore the decision makers need to have a clear understanding of the current & future state of market place & economy and impacts of IT. There have been 3 important streams of research works on IT adoption. They are:

- Research based on TOE framework (Tornatzky et al. 1990) rooted on theory of DOI (diffusions of innovations) (Rogers 1995) explaining the adoption and implementation of technology innovations at the firm level. As per the TOE framework, three contextual elements of any firm viz. technology, organization, and external environment influence the adoption decisions of technology.
- Research focused on technology adoption, not from the context of decision to adopt, but from the view of adoption process itself. Examples include TAM (Venkatesh & Davis 2000), Eight Rung Ladder Model (Farbey et al. 1995), IS Effectiveness Matrix (Seddon et al. 1999) etc.,
- Research focused on the success factors of information systems, the most popular ones being DeLone and McLean Model (Delone & Mclean 1992, 2002, 2003) which explores 6 dependent variables of IS success and the subsequent work by Petter et al. (2013) identifying 43 independent variables that influence the different dimensions of IS success.

2.2 Healthcare Specific IS Adoption Research

In line with the above streams, few research works on IS adoption in the context of healthcare analytics also have been carried out in the past. Ghosh & Scott (2011) conduct an in-depth study on cardiac surgery programs in a major hospital to find out the antecedents and catalysts for developing a healthcare analytic capability. The focus of the research was more on the data side. In reality, though data is an important ingredient, its capabilities alone cannot influence the adoption of innovative technologies such as HA, because there also exists other technical, organizational and environmental factors (Tornatzky et al. 1990). There are some other works focussing on adoption of electronic health records (Adler-Milstein & Jha 2014; Angst & Agarwal 2009) in hospitals, but they do not discuss the next step of leveraging the data for better decisions and outcomes, which is the core of healthcare analytics. Organizational and management support are some of the important factors in adoption decisions. Bhattacherjee & Hikmet (2008) focus specifically on the healthcare segment and use the TAM model (Venkatesh & Davis 2000). Lancry et al. (2001) consider analytics adoption by payers in the healthcare industry; HCO were not considered in that work. Brooks et al. (2015) develop a healthcare business intelligence maturity model, which provides a broader perspective on the subject covering organizational, people, and technology processes specific to complexities healthcare. However, the focus of the model is on maturity assessment of existing BI implementation of healthcare and hence cannot be used as a decision model.

Van Der Meijden et al. (2003) based on their empirical research identify the determinants of each of the success factors in D&M model. However, their findings reveal that some of the determinants do not fit into D&M model, especially in the case of IS failures attributable to contingent factors such as organization culture etc., There is a healthcare IT evaluation model called HOT- fit model (Yusof et al. 2008 a, 2008 b) that attempts to address some of the above issues by integrating the D&M and IT Organization fit models. They highlight the importance of considering aspects of technology, human and organization in evaluation of healthcare IT. The problem with this modified model is the confusions arising out of changes in dependency between the factors owing to changes in core constituents of D&M Model. Yu (2010) in his research work also describes the HOT-fit model as "the extension of the original D&M IS success model", where the causal relationships among the constructs in the D&M model is mixed with the concept of 'fit'". Yu (2010) proposes a multi-method (qualitative & quantitative) approach to evaluate healthcare to address the limitation of HOT-fit model by introducing concept of psychometric measurement theory and quantitative measurement for both cross sectional and longitudinal benchmarking of performance and impacts. But the inherent weakness of both of the above models is that, they do not take into consideration the industry and external environmental factors such as competitive pressure and healthcare regulations that influence the adoption of HA. Bonney (2013) based on literature review explores the key benefits, challenges, and obstacles of incorporating the BI technology into EHR so as to improve the quality and safety of healthcare delivery, but does not propose an adoption model. Interestingly, we could find only one research work on modelling for HA adoption based on TOE framework (Malladi & Arbor 2013).

Based on our review of the literature, we conclude that there is no decision model available which holistically covers technology, organization, people and external environment and hence there is a definite need to develop such a holistic framework or a model for HA, which can be used by industry to make informed decisions on adoption. Ammenwerth et al. (2003) highlight the three main problem areas or challenges in evaluation of healthcare IT i.e. the complexity of the evaluation object, the complexity of an evaluation project and the motivation for evaluation. While they advocate a need of a broadly acceptable framework, owing to nature of each information system in healthcare being very unique, they suggest narrowing down by defining the environment, as one size does not fit all. In keeping up with the view, the model that we develop would be specific to HA and include those variables, which are more relevant to the area of research.

3 HEALTHCARE ANALYTICS ADOPTION-DECISION MODEL

We propose our approach to building a HA adoption decision model in two steps. First, we will build a foundational typology in terms of identifying the major group of practical applications of HA (Section 3.1). Then, in Section 3.2, we propose our model and validate the applicability of the TOE framework variables in the context of HA.

3.1 Building Health Analytics Typology

Weigel et al. (2013) carried out a detailed typology study of healthcare technology based on the past 10 years research and the HA was identified as one of the themes of research. Adding to the above contribution, our objective is to create a typology of applications of HA at the next level, which will be used as the basis for our future investigation.

The HA adoption is driven by number of sources of the healthcare data such as EMRs, laboratory systems, diagnostic or monitoring instruments, insurance claims/billing, pharmacy, human resources and supply chain and real-time locating systems. HA is used in the areas of clinical and real-time clinical decision support, patient care, supply chain optimization and asset optimization (Ward et al. 2014). Also, HA can also contribute in number of other areas such as evidence-based medicine, genomic analysis, pre-adjudication fraud analysis, device/remote monitoring and Patient profile analysis (Raghupathi & Raghupathi 2014). Zhang et al., (2013) identify 3 types of clusters in health information technology applications in hospitals viz., clinical IT, administrative IT and strategic IT.

Using Ward et al.'s (2014) and Zhang et al.'s (2013) analysis of the health care architecture as the basis, three broad areas where the analytics solutions could potentially be applied are identified – clinical performance, operations performance and enterprise performance. However, based on the profile of the application listed by Zhang et al., (2013) and the areas where analytics can be leveraged, we further subdivide the clinical IT in to clinical decision support and clinical operations, because they pertain to different areas of processes within a hospital. Also one of the key emerging areas in HA is the analysis of the data generated outside the HCO which are not covered by Ward et al. (2014) and Zhang et al., (2013). Examples include public health data, EMR data on cloud, and social media data etc., Hence, based on our survey, we create a typology of HA application domains as shown in Table 1, where we also provide a brief view of 5 types of data with references to the literatures from the past.

Healthcare Analytics Applications	Type of Data	Few References
Clinical Decision Support	Medical history, laboratory results, clinical findings, medication, adherence and non adherence Range of data from images (e.g., magnetic resonance imaging) to numbers (e.g., vital signs) to text report (result interpretation) etc.,	(Shneiderman et al. 2013; Rojas et al. 2011; Wang et al. 2011; Berry and Milosevic 2013; Bohlouli et al. 2014; Post et al. 2013; Caron et al. 2013)
Clinical Operations	Meta data on lab testing, data from instruments used for diagnostics & monitoring, Radiology and pharmacy management data etc.,	(Songthung et al. 2012)
Administrative	Patient waiting time, CRM, financial, billing and insurance claims, scheduling resources, & controls, real-time location of assets or systems, Email, RFID, supply tracking etc.,	(Kudyba and Gregorio 2010; Srinivasan and Arunasalam 2013; Peck et al. 2014; Demir 2012)
Enterprise/ Strategic	Data pertaining to supply chain, HR, inventory management, financials, costing, reporting, hospital performance management, Customer management, customer satisfaction, marketing etc.,	(Aktaş et al. 2007; Xiang et al. 2015; Curcin et al. 2014)
Inter-organizational	Health Information Exchange (HIE), EMR, Public health data, data on epidemics, social media data etc.,	(Abouzahra et al. 2014; Kamel Boulos et al. 2010),

Table 1. HA Applications Typology.

3.2 Building HA Adoption-Decision Model Based on TOE Framework

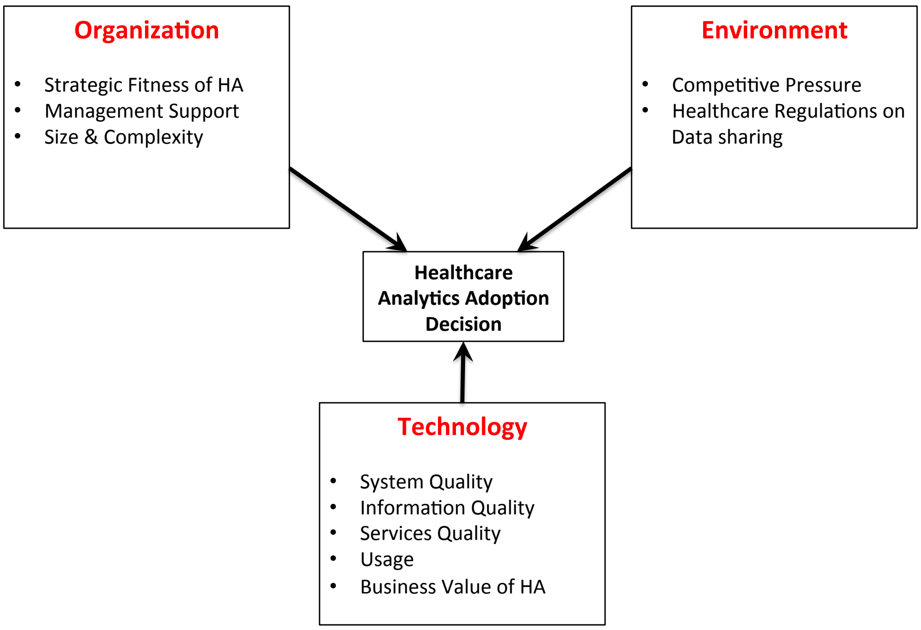

Figure 1. Healthcare Analytics Adoption-Decision Model

Research has indicated that unlike its precursors, analytics can be successful only if the entire organization is involved. Even early on Davenport (2006) has indicated that analytics projects be undertaken as an enterprise activity. Gillon et al. (2014) discuss the depth of management challenges in the context of 4 Ds (decision rights, dollars, department roles & delivery) that organizations need to overcome in order to exploit analytics systems. This is perhaps because the performance enhancement through analytics is expected to manifest across the entire value chain. This view is also echoed in recent research by Barton & Court (2012) who see IT architecture, modelling and organizational transformation as three important pillars of successful deployment of analytics. Thus, specifically, a HCO considering an HA adoption-decision has to look at the current and future state of the organization and environment, in addition to the technology itself. This point motivates our use of the TOE framework (see Figure 1), since it does touch upon all these elements and also provided the flexibility for incorporating contextual factors impacting adoption. Table 2 below summarizes the past research in terms of application of TOE framework and the variables used.

Application Area	**Variables Used for IS Adoption**		
	Technological	**Organizational**	**Environmental**
ERP (Bradford & Florin 2003)	Compatibility, complexity, Business Process Reengineering	Management support, objectives consensus, Training	Competitive pressure
e-procurement (Soares-Aguiar & Antonio 2008)	Competence	Scope, size	Competitive adoption, partner readiness,
SME adoption of IT (Ramdani et al. 2009)	Relative advantage, complexity, compatibility, trialability, observability	Executive support, readiness, IS experience, size	Industry, market scope, competitive pressure, external IS support
SME adoption of IT (Thong 1999)	Compatibility, complexity and relative advantage	Size, knowledge and information intensity.	Competition
EDI (Kuan & Chau 2001)	Perceived direct & indirect benefits	Perceived financial cost & technical competence	Perceived industry & government pressure.
e-business (Zhu & Kraemer 2005)	Competence	Size, international scope, financial commitment	Competitive pressure, regulatory support.
e-business (Zhu et al. 2006)	Competence	Scope, size	Competitive pressure, customer readiness

Table 2. TOE variables In Past IS Adoption Research.

3.2.1 Technological Context

Based on the past TOE framework based research for IS Adoption (refer Table 2), we include in our model the availability and characteristics of the information technology both internal & external to the healthcare organization and we also use the independent variables guided by D&M model (system quality, information quality, services quality, IT usage, business value of HA) within the context of healthcare analytics.

Table 3 below describes these variables in detail. It has to be noted that D&M model is a IS success model which deals with the quality aspects of the system, information and services getting converted into benefits for the organization through effective usage of technology. HA system overlays on top of the existing data assets and hence it cannot exist in absence of rest of the hospital information systems. As a corollary, adoption of HA from a technological context also majorly depends on the maturity and quality of the existing systems. Hence even from that perspective the integration of D&M model into the TOE clearly serves our purpose.

TOE Factor	D&M Factor	Healthcare Analytics Attributes
Technology Availability	System Quality	Qualities of the Systems (Hardware, Network, Applications, Database, Model Management, Analytics Engine, Data warehouse systems): Ease of use, system flexibility, availability reliability, performance, sophistication, flexibility, response time, scalability, Security etc.,
	Information Quality	The consumable outputs from the systems: Data accuracy, representation, presentation, dashboards, data quality, consistency, data timeliness, currency and relevance of the Analytics reports produced by the applications and systems.
Technology competence	Services Quality	Service strategy, service operations, services design, continuous services improvement, SLA management, communication, relationships, empathy, responsiveness, technical competency, Analyst competency
	Technology Usage (Actual Use & User Satisfaction	Purpose, extent and frequency of use of Analytic reports to support decisions, motivation to use. Clarity in expectations, satisfaction, involvement in enhancing the quality, feedback
Benefits	Business Value of HA (Net Benefits)	Clinical Decision Support, reduction in mortality, reduction in clinical errors, improvement in patient care & handling, cost and operations optimization, reduction of material, manpower & time wastages and profitability and reduction of procedures, optimized use of healthcare test and monitoring equipment etc.,

Table 3. Mapping of D&M IS Success Factors to Healthcare Analytics

3.2.2 Organizational Context

Baaed on the past TOE framework based research for IS Adoption (Refer Table 2), we include in our model the characteristics of the organization with respect to implementation of new technology and take three important variables relevant for HA viz., strategic fitness of HA, the managerial support and size & complexity.

Strategic Fitness

For the HA investment to create value to HCOs, the most important prerequisite is a proper alignment of IT and Business. By alignment we mean that IT investments and capabilities need to be aligned to market and patient (client) needs. Henderson & Venkatraman (1999) proposed strategic alignment model for business-IT integration, which describes two types of integrations (i) strategic Integration that links business strategy with IT strategy and (ii) operational Integration that describes the integration of organizational business processes and IT Infrastructural processes. Based on their research with 15 hospitals in US, Bush et al. (2009) posit that the alignment of information systems with organizational objectives and strategies is a key, contemporary challenge to organizations in general and the health care industry in particular. They also characterize the alignment in a simple, but critical 5-step process (Identify organization objectives, identify organization strategies, envision IS, gain approvals, acquire & implement) to enable CIOs check themselves before investing in IT.

Managerial Support

One of the very critical factors for success of any IT implementation is the executive or management support in the organizations (Jarvenpaa & Ives 1991). With HA, this becomes more relevant because the target users for this technology are actually managers themselves. So, they need to believe in decisions support through analytics, promote and encourage the user adoption, invest in hardware, software and services, drive & encourage skills enhancement of data analysts. Armstrong & Sambamurthy (1999) in their research, based on a large empirical survey highlight that CIO's membership at the top layer of management is critical and his constant collaboration with the top layer promotes the IT awareness, knowledge and assimilation. Similarly, with the increased criticality in the role of the information systems in the modern technology driven organizations, the senior business managers are now expected to show stronger leadership (Bassellier et al. 2003) to support deployment of IT. The above highlights the importance of considering the softer aspects of management support in HA adoption.

Organization Size

The larger the size and more complex the HCOs are, it is more likely that the organizational decision process would need the support of HA to ensure accuracy and timeliness in decisions. Shim & Lee, (2010) in their study posit that any large scale IT investment decision is more salient in larger organizations rather than small organizations and the decision making behaviour has relationship to the size of the firm. The assimilation of information technology (Bajwa et al. 2008) and also the IS success resulting from the usage have a direct correlation to the size and maturity of the firm (Raymond 1990). There are also research works that have identified a weaker significance of organization size to IS adoption (Gremillion 1984; Hameed & Counsell 2014) and one other that has identified stronger significance (Ifinedo 2007). Nevertheless, we take the HCO size as an important factor that influences the adoption of HA since there are more studies advocating a positive correlation between them.

3.2.3 Environmental Context

Baaed on the past TOE framework based research for IS Adoption (Refer Table 2), we include in our model, two important factors in the context of external environment that influence the adoption decision viz., healthcare regulations on public health data or EMR/clinical data sharing and competitive pressure.

Competitive Pressure

Past research indicates that the competition in markets can positively influence the innovation and adoption of new technologies (Rogers 1995). Also a dominant player in that competitive value chain can influence the rest to innovate (Kamat & Liker 1994) and in growing industries (like healthcare) the innovation happens even more rapidly (Tornatzky et al. 1990). Research has proven that the investments in information technology create competitive advantage leading to superior performance (Kohli & Devaraj 2003; Melville et al. 2004). One critical point to note here is that investments in technology to gain competitive advantage should be linked to the technology strategy, (which is an outcome of IS-business alignment). Porter (1985) says, “Technology strategy must reinforce the competitive advantage a firm is seeking to achieve and sustain. The most important technologies for competitive advantage are those where a firm can sustain its lead, where drivers of cost or differentiation are skewed in its favour, or where the technology will translate into first-mover advantages.” We conclude here that, the competitive pressure pushes the HCOs to adopt better technologies to provide better healthcare.

Healthcare Regulations on data sharing

Within the emerging context of the digitization of health care, electronic medical records (EMRs) constitute a significant technological advance in the way medical information is stored, communicated, and processed by the multiple parties involved in health care delivery (Angst & Agarwal 2009). While even in developed countries like US, while there has been a support from Govt. researchers highlight the slow adoption rate of EMR data exchange (Adler-Milstein & Jha 2014). The availability of clinical data sharing eco-system becomes an important factor for adoption of the analytics technology, because for every HCO, the availability of clinical data of the patients across the population is of significant value that can help reduce their learning curve and proactively analyse data for patterns. There are also a number of challenges in EMR like (i) data privacy concerns (Angst & Agarwal 2009) especially when the data delivery model is on cloud (Fabian et al. 2014); capability to extract data even when data is available and; lack of adoption of common data structures across the vendors (Ward et al. 2014). We foresee that, in countries where the clinical data sharing eco-system is good, there is a possibility of better adoption of healthcare analytics as compared to countries where it does not exist. In summary, clinical data sharing becomes an important consideration in evaluation of adoption of healthcare analytics.

4 RESEARCH METHODOLOGY

Recognising the contemporary nature of the study, nascent stage of analytics adoption in healthcare, the innovative nature of this project investigating the health analytics adoption decision to support a given performance domain in hospitals and the nature of research questions, a qualitative case study approach is considered suitable (Yin 2009). Even though analytics software solutions are available in the marketplace for business organizations, their adoption in healthcare context is limited and still in an exploratory stage. A case study method, taking a multiple stakeholders perspective, is employed to understand the phenomenon at organizational as well as at individual levels. The objectives is to understand and explore the antecedents, barriers and inhibitors in the adoption of analytics solutions and map the relationships between various antecedents in the adoption decision, and the performance domain that is supported by a typical analytics software solution. Taking into consideration, the preparedness of the health care institutions, experience of adopting generic IT solutions, types of operational and structural changes required for effective adoption and use of those solutions, users' attitudes and behavioural changes required and organizational and contingent variables, the aim here is to explore why a case organization adopt certain specific features or components of the analytics solutions to support a particular performance domain while ignoring the others. In addition, it will document the phenomenon of the antecedents for adoption decision and the interacting influence of various organizational, environmental and technology factors on the adoption decision.

Data is collected primarily through semi-structured interviews. The objective is to collect information about four key aspects i) scope, relevance and organizational context of each of the performance domains (clinical, operational and strategic), ii) organizational, environmental and technology related factors that could influence the adoption decision, iii) factors influencing the people's behaviour and attitude towards the potential adoption and use of analytics solutions in their organizations and iv) inter-relationships and interacting influence of each of these factors in the context of adopting an analytics solution and their potential impact on espoused health and performance outcomes. At the organisational level, the focus will be on the origin, evolution and use of various information technology solutions in the past, IT-Business alignment, data sharing culture, and interconnectedness of their existing systems, business changes the organization is generally prepared to make in the context of adopting analytics solutions, and the associated implications for organisational structure, processes and people. The focus at individual level will, however be on their role, identities, skill levels, knowledge of the impact of potential analytics solutions, their attitude towards the analytics solutions, their ability to shape practices and policies in the context of the adoption and use and their perceived implications for skills, structures, processes and performance outcomes in this new analytics based decision making environment.

Appropriate validation efforts such as checking for research effects and biases, providing interview manuscripts to respondents, getting feedback from respondents and triangulation of data are carried out to improve the data quality. The data is analysed in an iterative manner with data collection and has identified emerging themes. Next section presents the results, discussion and the findings.

5 RESULTS, DISCUSSION & FINDINGS

5.1 Background of the case study organization:

Case study organization is a medium sized (200 bed) hospital in India that has been embarking on the journey of implementation of HA and also had some initial success. The hospital has 6 centres in different cities and also uses 3 different types of HMS. The backend is a Microsoft SQL database and they use inbuilt tools for reporting and data analysis. The scope of the case study was to validate the typology of healthcare applications as tabled in the section 3.1 and also get a high level point of view of the hospital on the antecedents of HA adoption-decision.

Interviews were conducted with the CEO/Joint Director of the hospital, the lead critical care consultant doctor (CCC) and the data analyst (DA). Using the semi-structured interview protocol developed earlier, interviews were conducted and data was collected. The interview was of 60 minutes duration and was recorded with prior permission from the organization and key respondents. Interview questions were loosely structured, allowing respondents flexibility in responding. The interview started with the introductions and brief explanation of the scope and objectives of the study. Each respondent was asked to provide some information about their background – past experience, qualifications and the role they play in the hospital and their views and expectations on the health analytics in general. Further two main questions were asked to understand the context and their perspective on health analytics solution. The first question was meant to elicit respondents' views and information about the variety of data captured, maintained and used by the hospital and their technological conditions and constraints. The second question was meant to understand the key antecedents for the adoption of health analytics solution in the hospital from the respondents' point of view. They were asked to respond to each of the factors in the model – organizational, technological and environmental factors.

5.2 Typology of HA applications

Even though the hospital is of medium size (200 bed hospital), the breadth and scope of the clinical and patient care activities carried out in the hospital is significant. Case study hospital is capturing a variety of data. Clinical data that includes laboratory data, pictorial data (images) from PACS, graphical data from ECG, diagnostic data, and a huge data set of scanned copies of patient case sheets maintained in DMR.

In addition, it has operational data that incudes patient demographic data, patient history and price & cost of treatments; and administrative data that covers revenue data, human resources data, inventory and marketing data. In addition CRM (customer relationship management) data such as voice response data from monitors and machines, though is available is not captured efficiently. The data collected is internal and the hospital has neither access nor capabilities to collect or retrieve public health data and/or the data from social media. The data thus collected though has a variety in terms of the text, voice, images and paper/scanned, the hospital appears to be deficient in terms of integrating the data and facilitating easier sharing of the data across the hospital for clinical and operational decisions.

Thus, though a wide variety of data is captured and maintained in the hospital, it is in a silo form and hospital does not have efficient systems and processes to facilitate sharing of that data across the hospital. Even though electronic medical record (EMR) systems are in place, the hospital does not capture the vital notes and information recorded by the doctors and nurses on the patient records. Even though the patient records are in so called 'electronic' form, in reality, it does not contain useful information for making clinical decisions and to support hospital decision-making processes. Full and effective adoption of EMR is not observed in this hospital. According to literature, EMRs are an important antecedent for the effective adoption of health care analytics solution and use for decision support. Limited adoption of EMRs may actually limit this hospital's ability to use the analytics solutions effectively even after they are adopted.

5.3 Technological context:

The factors relating to the health care analytics technological context that could influence the adoption decision as identified in the model are quality of the system itself, quality of the information produced by the system, quality of the service delivered by the system to the users and the actual usage influenced by the ease of use, usability and availability. In addition, perceived business value of health care analytics is also considered to be an important determinant. As expected, business value of adopting Health care analytics solution is a critical factor in this case study organization. Pointed out by a key respondent, "*any analytics should result in some decision which either improves the profitability, reduces the cost of the patient or improves the safety"* The business value in this case, however, includes not just the bottom line of the hospital in terms of its profitability typical to any business organization, but also the clinical and health outcomes.

In the absence of any exposure to real HA solution to these respondents, observations with regard to the quality or potential quality of the HA system are limited. Raising the issue of information quality and its potential use, one key respondent defined analytics as *"organizing the data in a structured way and presenting it in a readable for so that… will be able to take decision …"*. So, if the system is either not capable of presenting the data that is easy to read and presentable and importantly relates to the type of decision it is expected to support, the value of HA solution is diminished. Highlighting the importance of 'usage' and the lack of skills to adopt modern sophisticated techniques to interpret the analysis and results, key respondent made this observation. He said, "*we have all the data , trending and everything, but we don't know if it is statistically significant or not*". Thus, level of adoption and effective use are also considered important factors affecting the adoption decision. Managements, as expected, would not knowingly make an adoption decision in a technological context, if they are not prepared to use it effectively and if they are not prepared with necessary skills and training. It is observed as peer the key respondent, "*we have a performance analysis system, which is very subjective currently. So, I will not say the data is very clean & right actually."* This points out the futility of having a data that the management cannot effectively analyse and use it for performance improvement. Thus, usage in general and ability to use in particular are observed to be critical antecedents for the HA adoption decision.

The finance and company directors use administrative data captured and maintained by the hospital. Talking about the actual decisions carried out based on data the CEO said "… *results are tangible in operations data… whereas, in clinical data the outcomes are not tangible or immediate…. which will happen over a period of 6 months… which the doctors or a nurse will not be able to perceive it. So, they are not making it as a priority…".* Though a HA analytics solution has capabilities to support decision making in both clinical as well as operational management, it will first be used for operational performance improvements. Considering the general resistance to change by the medical profession, perceived impact of these technology solutions on their independent judgment and power relationship in the overall health care management, hospital top management prefers to start its application to operational issues first.

Quality of information captures and stored in the hospital that could be used as an input to an HA analytics solution is an important factor affecting the outputs produced for decision support. Commenting on the data quality, it is observed, "*…in the data structure lot of confusions are there. We have to do a lot of cleaning work before we try to do some kind of analytics."* (Data Analyst). As pointed out by another respondent, "*the clinical data entry is not that easy… the software is not user friendly*" and that data is heterogeneous and there are no standards. This highlights the importance and impact of information quality on the adoption decision and its potential use. As rightly summarised by another respondent, "*I think I would generally divide peoples approach into attitude, skills and knowledge…",* the attitude and behaviour of the users as noted in this study, has an impact on data quality and use, and may further affect the quality of decision support a HA solution could offer.

While technological capabilities of the HA solution are an important factor in the adoption decision, it is important to be aware of the limitations of the technology solution. If the no real strategic fit is achieved, then the problems in terms of adopting them to the organizational needs and using them to support decision making becomes hard and challenging. Some managers, however, would like an analytics tool to be fool proof and does everything the firm needs. As noted by the key respondent in this case study, "*the best analytics tool…should be fool proof. Any fool should be in a position to use it*". This observation, though appears a 'bit naïve' and raises the old spectre of 'technology' a panacea to all the problems, it raises an important dimension of use – that it should be easier for the user to use it and use it effectively. This is especially so in a context where managements are struggling to demonstrate effective returns on IT investments.

5.4 Organizational context

Strong management support and strategic fit are key antecedents in many technology adoption decisions and HA solutions are no different, the study found. Reflecting the importance in the case study organization, CEO has indicated his belief and passion about the use of IT in healthcare in general. He said, *"I am a clinician. I am promoter and also passionate about IT."* Good understanding of the need and importance of information technology solutions in health care context, and the information required for managerial and clinical decisions is essential to facilitate positive environment for HA adoption. As noted by the CEO, "*I know what each role wants"* and therefore is in a better position to be a champion in the adoption of technologies. Given his role as a CEO and Joint director for the hospital, he has the capacity to influence the adoption decision as expressed in his own words. He has "*a reasonable power to make a technology adoption decision"* in the hospital. The need to address various stakeholders in an organization and their clarity with regard to the expectations of health analytics are clearly visible in the case study.

Talking about the decision factors, the management would consider if it were to invest in analytics, one key respondent noted that, "*The major factors which will determine our implementation of analytics will be three things -: one is availability of a tool… second is the cost… the third is third thing is I do not know the extent of analytics that can be done…"* Thus, the availability of a 'suitable' analytics solution, and the knowledge on the type and nature of analytics application for a range of decision support situations in a hospital are important antecedents influencing the adoption decision. This once again reinforces the importance of strategic fitness of HA solution to organizational needs and the effectiveness of evaluating such fitness is dependent upon the knowledge and skills of the hospital top management.

As expected size and complexity of the hospital operations are important determinants in the adoption decision. Talking about impact of size on adoption decision, the CEO said "*any hospital with more than 50-60 beds will definitely need analytics"* and *"less than that the hospital owner or promoter knows most of the things which is happening."* But he also added "*if the hospital grows bigger analytics would be useful.*"

5.5 Environmental context:

In our model we identified the competitive pressure and healthcare data sharing regulations as antecedents to adoption from the environmental context. Talking about the impact of competitive activities in the industry driving hospitals adopt new technologies, the CEO said, *"Naturally, what my peer is doing, what my competition is doing, I would like to adopt if my competition is really doing it."* Responding to the question on impact of healthcare data sharing regulations, he said, "*The problem … is that there is no standardisation…. there is no rule that I should share my data except for some critical information on infectious diseases…"* and "*I do not share my data with others*". He also said *"we do not get right information through public data …*" and "*public health data can be used by doctors and their approach to diagnostics can change*". This response is in line with our literature reviews that indicate that the adoption of Health Information Exchange is low. The CEO also added "*data sharing culture helps in adoption".*

6 IMPLICATIONS

Managerial Implications

Our initial research has important implications for management. First, it provides a useful framework for managers to assess the conditions under which analytics is adopted to better realize business value. Second, the exercise of understanding the existing data infrastructure itself helps managers visualize the potential applications of healthcare analytics and possible business cases for adoption. Our case study also reveals that one of that the most challenging prerequisite for adoption healthcare analytics is the availability of data in electronic form and also its quality. Third, our finding indicate that a decision maker needs to recognize the fact that the HA adoption is not just a technical decision and many organizational and environmental factors play a role in its success. Fourth, HCOs can easily get distracted from what is actually required by their organization, if they do not have clarity and a strategy around the adoption of healthcare analytics. Our research aims to provide the needed clarity and inputs for their strategy. Fifth, our case study findings indicate that the analytics adoption need not be a big-bang approach and the same becomes easier where there are tangible and short-term results based on implementation of operational analytics. This gives a direction to HCOs where to start the adoption of analytics and quickly demonstrate the business value. Sixth, for managers from healthcare solution vendors', this study provides insights into the industry, market's view on HA adoption factors, the adoption patterns, challenges & hurdles HCOs face and guide the future design of their products and solutions to address the specific issues in the industry.

Research Implications

Our research has many implications to the academic world. Further to our study, there is a scope of using the case study artefacts and create instruments for evaluation of HA readiness and adoption based on design-science research theory (Peffers et al. 2008). The D&M Model in the context of HA, can be extended for post implementation success evaluation also. Study of the critical success factors for HA and antecedents of user adoption would also be possible extensions of our study. Specific issues pertaining to impact of data quality and availability can also be explored further. In summary, our study provides a starting point of expanding the knowledge and the understanding of the aspects of the HA adoption in its current nascent stage.

7 CONCLUSIONS

We established the need for an adoption-decision model for HA and contributed in proposing a typology of HA applications. Our adoption model used the TOE framework and D&M IS success model. Using a case study, we also validated this model and presented our findings. However, a single case study is not sufficient to formulate a model that can be valid for different types of environments. There are differences in practices in healthcare delivery between country to country and between private and public HCOs. Hence, we would like concluding that, the current study on healthcare analytics adoption is just the beginning in the formulation of a new stream of studies to follow, especially keeping the fact that the issue of evidence-based healthcare delivery has a major societal impact.

Appendix A

Structured Interview Questionnaire

The following questions comprise our interview. Suitable follow-up questions were also asked to avoid bias in the interview process, although specific transcripts of the interview are not included owing to space limitations.

Questions

1. Please tell us about your background, your current role and responsibilities.
2. Please tell us about your existing types of data infrastructure in your organization
3. What type of the data fall into clinical, operational and administrative categories
4. Please tell us about any other types and categories of data that we have not covered.
5. Who uses these data and how?
6. Please tell us how the use of the data helps to make clinical, operational and strategic decisions.
7. What kinds of reports are prepared for the senior management?
8. What factors in your opinion could potentially influence your hospital's decision to either adopt or not adopt analytics? Please respond to this question with reference to technological factors such as availability and competence; organizational factors such as size, managerial support and overall strategic fitness of HA and; environmental factors such as competition, and regulations.
9. Can you to share anything else important that we have not discussed?

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