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Two Essays on Analytical Capabilities: Antecedents and Consequences

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Two Essays on Analytical Capabilities: Antecedents and Consequences

A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy in Business Administration

by

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ABSTRACT

Although organizations are rapidly embracing business analytics (BA) to enhance organizational performance, only a small proportion have managed to build analytical capabilities. While BA continues to draw attention from academics and practitioners, theoretical understanding of antecedents and consequences of analytical capabilities remain limited and lack a systematic view. In order to address the research gap, the two essays investigate: (a) the impact of organization's core information processing mechanisms and its impact on analytical capabilities, (b) the sequential approach to integration of IT-enabled business processes and its impact on analytical capabilities, and (c) network position and its impact on analytical capabilities.

Drawing upon the Information Processing Theory (IPT), the first essay investigates the relationship between organization's core information processing mechanisms–i.e., electronic health record (EHRs), clinical information standards (CIS), and collaborative information exchange (CIE)–and its impact on analytical capabilities. We use data from two sources (HIMSS Analytics 2013 and AHA IT Survey 2013) to test the theorized relationships in the healthcare context empirically. Using the competitive progression theory, the second essay investigates whether organizations sequential approach to the integration of IT-enabled business processes is associated with increased analytical capabilities. We use data from three sources (HIMSS Analytics 2013, AHA IT Survey 2013, and CMS 2014) to test if sequential integration of EHRs –i.e., reflecting the unique organizational path of integration–has a significant impact on hospital's analytical capability. Together the two essays advance our understanding of the factors that underlie enabling of firm's analytical capabilities. We discuss in detail the theoretical and practical implications of the findings and the opportunities for future research.

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CHAPTER 1

INTRODUCTION

Business analytics (BA) capabilities are increasingly seen as the enabler of organizational performance (e.g., Agarwal and Dhar 2014; Davenport et al. 2010). As a consequence, academics and practitioners are focusing their attention on ways to build analytical capabilities. However, current theoretical understanding of the antecedents and consequences underlying firm's analytical capabilities remain underdeveloped. The primary focus of the dissertation is to uncover the antecedents and consequences of analytical capabilities that are yet to receive due attention in information systems (IS) literature. By doing so, we intend to enhance our understanding of how firms can leverage business analytics and can potentially turn it into organizational value. Since BA is in a preliminary stage of gaining awareness and adoption, the findings can potentially shed light on the theoretical underpinnings explaining the differential ability to leverage analytics in organizations. Furthermore, the two essays build on and reconcile two divergent streams of IS research–i.e., business analytics and healthcare information technology (HIT). Business analytics is seen as a key enabler of the digital transformation of the healthcare industry. The uniqueness of the healthcare domain and challenges associated with HIT implementation represents a significant context worth of examination. Specifically, in the healthcare domain, there is a paucity of theory-driven research that investigates the role of BA capabilities on healthcare performance metrics. Taken together the two essays address call to more theory-driven research to enhance our understanding of BA capabilities in the healthcare context. The two essays are elaborated in the next few subsections.

Essay 1 investigates the role of organization's information processing approach and its implication on firm's analytical capabilities. Employing a well-established organizational lens,

Information Processing Theory (IPT) (Galbraith 1974; Tushman and Nadler 1978), we argue that organizations evolution of analytical capabilities is path dependent on firm's information processing approach–i.e., organizations ability to address uncertainty by increasing information flow and developing information processing capabilities. We argue that certain information processing mechanism have significant implications on enabling analytical capabilities. We identify three such information processing mechanisms–i.e., *extent of EHR use*, *clinical information standards*, and *collaborative information exchange*–as plausible mechanisms through which firms enable analytical capabilities. Specifically, we contextualize the IPT framework to the healthcare domain by identifying healthcare information processing mechanisms that can potentially influence firms' analytical capabilities. We test our hypothesized relationships using two secondary databases–*HIMSS Analytics 2013* and *AHA IT Survey 2013*–consisting of HIT implementations in more than 5000 U.S hospitals.

Essay 2 investigates the organizational approach to the integration of core business process and its implication on analytical capabilities and organizational performance. We argue that sequential integration of healthcare IT reflects distinct paths of EHR integration and could potentially explain the difference in analytical capabilities above and beyond other indicators. The paper draws on the competitive progression theory (Rozensweig and Roth 2004) as the guiding theoretical lens to develop a conceptual model that examines if the sequence in which hospitals integrate EHRs has implication on analytical capabilities. Furthermore, we investigate if such a pattern of integration can influence healthcare performance (i.e., quality of care) through analytical capabilities. Using an event sequence analysis, we empirically test the conceptual model using a merged dataset of U.S. hospitals.

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CHAPTER 2

ESSAY 1: HOW FIRMS BUILD ANALYTICAL CAPABILITIES: AN INFORMATION PROCESSING VIEW

ABSTRACT

Business analytics capability is being increasingly leveraged in organizations to gain actionable insights and to improve decision-making. While business analytics continues to draw attention from academics and practitioners, little or limited theoretical understanding exists as to how firms build such capabilities. To realize value from business analytics, managers and researchers need to have a clear understanding of how an organization's analytical capabilities are built. Current understanding of analytical capabilities is limited and lack a systematic view. We propose analytical capabilities as key to improved firm performance, and our work examines and empirically tests the relationships among organizations core information processing mechanism –i.e., *extent of EHR use*, *clinical information standards (CIS)*, and *collaborative information exchange (CIE)*–and analytical capabilities in the context of healthcare. Drawing upon information processing theory (IPT), we examine the connection between the organizational approach to information processing mechanisms and its impact on analytical capabilities. We further examine whether and when different types of information processing mechanism independently and jointly influence analytical capabilities. We use a merged dataset ($N = 355$) to conduct a cross-sectional study of a large panel of U.S. hospitals. Using OLS regression analysis, our results indicate a positive association between organization's information processing mechanism used for addressing process uncertainties (i.e*., EHRs*, *CIS*) and relationship uncertainties (i.e., CIE) is associated with higher analytical capabilities.

INTRODUCTION

Organizations are increasingly leveraging business analytics as a key mechanism to derive actionable insights, spot trends, improve decision making and optimize business functions (Davenport 2006; Davenport and Harris 2007; Davenport et al. 2010; Holsaple et al. 2014; Negash and Gray 2008). Business analytics has been defined as "*the use of data to make sounder, more evidence-based business decisions*" (Seddon et al. 2012). The importance of the use of analytics can be judged by the fact that a recent survey found that CIO's gave higher priority to analytics initiatives compared to other performance enhancing technology categories (e.g., cloud computing, grid computing, mobile computing) (Gartner 2014). Also, a recent report by IDC suggests that analytics related market grew by 13.8% during 2011 to $32B, and is predicted to be at $87 billion in revenue by 2016 (IDC 2012).

Although benefits of business analytics are apparent, building analytical capabilities is a challenge (Agarwal and Dhar 2014; HBR Analytics 2013; Zheng et al. 2012). Analytical capabilities have been defined as "*organization's ability to undertake value-creating actions from the use of business analytics*" (Shank and Sharma 2011). Even though the volume of information is growing exponentially and BAs are becoming more sophisticated, BAs do not automatically translate into value for the organization (Pettrini and Pozzebon 2009; Oliveira et al. 2012). Organizations not only have to interpret a variety of information from old and new technologies but also have to deal with new form of structured and unstructured data (Prahalad and Krishnan 2008; LaValelle et al. 2013). This diversity of data structures requires ontological representations in a form that is machine-readable (Marcos et al. 2015; Amster et al. 2014). Same time, there is also a need for an increased level of process integration to access granular level organizational data (Caban and Gotz 2015). As sense making of this data becomes a priority,

organizations are pressed with the need to develop and build analytical capabilities. The ability to manage the enormity and complexity of data has been identified as a critical organizational capability for supporting evidence-based decision-making (Davenport and Harris 2007; Mithas et al. 2011; Pfeffer and Suftton 2006). While numerous organizations are rapidly embracing analytics, only a small proportion have been able to build analytical capabilities (Butermann 2008; HBR Analytics 2012; Watson and Wixom 2007).

The predominant focus of IS literature has been the business value derived from use of BA systems on firm performance (e.g., Davenport 2013; Isik et al. 2013; Popovic et al. 2012; Seddon et al. 2012). Specifically, the emphasis has been whether these systems contribute to business value (e.g., Malladi and Krishnan 2011; Seddon et al. 2012; Trkman et al. 2010) and the factors that influence BA adoption in the organization (e.g., Isik et al. 2013; Oliveria et al. 2012). Isik et al. (2013) identified data quality as the key factor in BA success. The high quality of data leads to increase adoption and success in adoption of BA technologies. Similarly, Popovic et al. (2012) also identified information quality and decision environment as factors in BA initiative success. Trkman et al. (2010) and Oliveria et al. (2012) examined if BA positively impacts supply chain performance. BA capabilities optimized supply chain processes thus directly influencing enhance supply chain performance. Shanks et al. (2010) also identified process optimization as the mechanism through which BA capabilities influence firm performance. Shanks and Sharma (2011) argue that BA capabilities lead to improved firm performance through the enabling of other dynamic capabilities (e.g., operational capabilities). However, since firms are increasingly using comparable BAs, it is essential to know the points of differentiation that lead to the development of analytical capabilities. While IS literature predominantly focuses on the mechanisms through which BA capabilities influence firm

performance (e.g. Davenport and Harris 2010; Eckerson 2012), clearly, there is lack of studies that articulate a theoretically grounded model that explains how firms can build BA capabilities.

Given the comparable nature of BA, business processes have been suggested as the possible differentiation factor that can explain the heterogeneity in analytical capabilities (e.g., Davenport 2006; Dehning and Richardson 2002; Melville et al. 2004). In the present context, business process refers to "*specific ordering of work activities across time and space, with a beginning and an end, and clearly defined inputs and outputs.*" (Davenport 1993). BA capabilities are increasingly associated with high level of business processes integration (Raghu and Vinze 2007). Given the path dependency nature of BA capabilities, it may be safe to assume that BA capabilities may not create business value by itself and must synergistically interact and integrate with multiple factors, particularly business process capabilities, to influence outcomes (e.g., Dehning and Richardson 2002; Melville et al. 2004; Wade and Hulland 2004; Nevo & Wade 2010). Although there seems to be a connection between BA capabilities and organization's core business processes (e.g., Olivera et al. 2012; Trkman et al. 2010), theoretical understanding of this link remains underdeveloped.

At a micro level, leveraging BA capabilities involves information processing of granular data derived from integrated business processes (Raghu and Vinze 2007). Information processing of organizational data is critical to addressing environmental uncertainties associated with dearth of data. For instance, organizations are part of the inter-organizational network. As a consequence, firms interlink business processes that enables collaborative exchange of information. The idiosyncratic nature of the relationships is the cause of uncertainties. Similarly, organizations experience uncertainties due to fragmented IT which constrains information flows and process coordination (e.g., Barua et al. 2004) causing further uncertainties. To alleviate

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uncertainty, firm's implement information processing structural mechanisms and information processing capabilities to enhance information flow. In other words, organizations building co-ordination mechanism to address the perpetual state of uncertainties. While certain types of uncertainty can have significant implications on firms' ability to leverage analytics, its impact on analytical capabilities remains underexplored.

Previous studies are limited in the ability to explain how organizational approaches to information processing interrelates with the various coordination mechanisms to influence analytical capabilities. We apply the information processing theory (IPT) (Daft and Lengel 1986; Galbraith 1977) framework to investigate whether and when different types of information processing (IP) mechanisms to address uncertainties (i.e., relational and process) in the health care context independently and jointly influence hospital's analytical capabilities. Three reasons motivate our effort to understand the theoretical mechanisms underlying analytical capabilities. Firstly, analytics supports key decision making (Buchanan 2006; Davenport and Harris 2007; Popovic et al. 2014). Secondly, business analytics is increasingly seen as strategic endeavor (Fonetella 2008; Gartner 2012). Finally, given limited resources, organizations need to prioritize their efforts to identify mechanisms that build analytical capabilities (SAS Analytics 2012; Seddon et al. 2012). Against this backdrop, this study attempts to provide a theoretically grounded understanding of firm's analytical capabilities by examining the connection between the organizational approach to information processing and its impact on analytical capabilities. The present research asks the following research question: how does different types of information processing capabilities–independently or jointly–impact analytical capabilities?

THEORETICAL FOUNDATION

The essay proposes that firm's analytical capabilities are function of organization's information processing approach–i.e., the alignment between information processing needs and the information processing capabilities associated with core business processes. We use the healthcare context as an arena to test our theoretical relationships. In the healthcare context, mandatory standardization of clinical and diagnostic processes results in low variations of business processes across hospitals (Chow et al. 2015; Gooch and Roudsari 2011; Kawamoto et al. 2014). Thus, a healthcare consumer is likely to go through similar clinical and diagnostic processes across different hospitals. Furthermore, standardization of healthcare processes also results in the standardization of information processing capabilities–e.g., EHRs - associated with these processes (Ozdemir et al. 2011). Given IP needs are closely connected to health care business processes (Gardner et al. 2014), it is appropriate to test it in the healthcare environment. Since healthcare business processes are generic across healthcare institutions, it is possible to compare hospitals in terms of the alignment between information processing needs and information processing capabilities. In this essay, we theoretically argue that organization's information processing approach plays a key role in influencing hospital's analytical capabilities. The essay seeks to identify IP mechanisms that have a significant influence on analytical capabilities.

Analytical Capabilities

Extant literature suggests that it is "the relationship between firm's information management practices and their business performance" (Mendelson and Pillai 1998, p. 432) that is critical to long-term organizational competitiveness (e.g., Mithas et al. 2011). However, it is the ability to leverage the information that differentiates one organization from others. In the

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context of this study, the analytical capability is conceptualized as an organizational capability. Hospital's analytical capabilities are formed over time by the implementation and use of BA functionality in combination with other organizational resources–e.g., expert knowledge, doctor's skill, paraprofessional experiences, process maturity, etc. Based on prior literature, organization's IT capability has been defined as the ability of the organization to mobilize and deploy IT resources in conjunction with other organizational resources and capabilities (Bharadwaj 2000). Specifically, such capabilities are evolutionary in nature and are developed over time through combinations of IT assets and other firm resources through practice and competencies (Aral and Weill 2007). While BA functionality may be generic in nature, BA capabilities are embedded within a firm and are very firm-specific. The source of strength of such capability is derived from this contextual firm-specific implementation, which makes it valuable (Bharadwaj 2000; Zhu and Kraemer 2002). In essence, BA functionalities are the tools/resources that are designed to support healthcare business processes, while analytical capabilities refer to the ability of the organization to leverage BA in order to enable superior performances.

Analytics in the healthcare context is associated with specific context sensitive information to guide inferences in three key areas: healthcare performance, clinical workflow, and process improvement (Tremblay et al. 2016). Analytics for performance is used towards achieving operational efficiency by managing process consistency through appropriate monitoring and evaluation to guide managerial actions (e.g., healthcare contract management, budgeting) (Caban and Gotz 2015; Westra et al. 2015). Analytics for clinical use is applied towards ensuring efficiency in medication management, patient care quality, population management, and medication safety. Increasingly, clinical analytics is used towards gathering

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and analyzing patient encounter data by developing rules based analysis that can detect unreported adverse drug events, measure adoption, implementation and efficient use of bar coding technologies, and also monitoring outcomes associated with patient care (Ferranti et al. 2011). Process related analytics is used towards identifying and correcting process inefficiencies and improving process quality (Smith et al. 2014). Based on the multi-dimensional nature of the construct, we define *analytical capability* as healthcare organization's ability to leverage business analytic tools (e.g., querying, online analytical processing, dashboards, reporting, data mining) to gain new insights related to healthcare performance, process effectiveness, and clinical care.

Information Processing Theory

The present research employs a well-established organizational perspective–*Information Processing Theory* (Daft and Lengel 1986; Galbraith 1977)–to understand the key factors that explain firm's analytical capabilities. Information processing has been defined as "*purposeful generation, aggregation, transformation and dissemination of information associated with accomplishing some organizational task*" (Stock and Tatikonda 2008). Organization's ability to take value creating actions and derive evidence based decision making is based on the firm's ability to analytically process the vast volume of organizational data from diverse sources (e.g., digital business processes, inter-organizational systems). Even though specific processes and information sources may necessitate various types of data transformation requirements, leveraging analytics involves information processing to derive these actionable insights. Accordingly, it is useful to view analytical capabilities from the perspective of organizational information processing theory (IPT). This IPT theory underlies the conceptual framework for explaining how firms build analytical capabilities.

The IPT posits that organizations need to align information processing capabilities and information processing needs to bridge the gap between the need for information and the organizational availability of information (Galbraith 1977; Tushman and Nadler 1978). By bridging the information gap, firms can reduce uncertainty. IP views information as a key organizational resource. To this extent, it is in efficient use of this information resource that is the most critical factor in organizational performance (e.g., Bhatt and Grover 2005; Cotteleer and Bendoly 2006; Davenport 1998; Davenport and Linder1994; Marchand et al. 2002; Mithas et al. 2011). The key focus of IPT is on the ways in which organizations structure information and the means by which this information is applied (Tushman and Nalder 1978).

IPT posits that effective utilization of organizational data requires an appropriate, context-specific combination of information processing mechanisms (Anandarajan and Arinze 1998; Andres and Zmud 1998; Argyres 1999; Cooper and Wolfe 2005; Gallivan et al. 2005; Premkumar et al. 2005). Since organizational design revolves around information flow within and beyond the organizational boundary, information processing mechanisms are pivotal structures that reduce context-specific uncertainty (Bensaou and Venkatraman 1995; Cooper et al. 2005; Chou et al. 2008). Thus appropriate context-specific structural mechanisms are necessary to mitigate uncertainty (Goodhue et al. 1992; Lin et al. 1997; Macpherson 2004; Zack 2007). The key emphasis is on the organizational design of information processing mechanisms as an effective approach to addressing various context-specific uncertainty. Thus, achieving effectiveness in the design of information processing mechanisms implies making a context-specific fit between information processing capabilities and contextual information requirements (Fairbank et al. 2006; Huber 1990; Tatikonda and Rosenthal 2000). The information processing mechanisms of an organization uses a combination of technological resources and structural

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design (Tractinsky et al. 1995; Stock and Tatikonda 2008). Hence, the distinct context requires a different combination of information processing mechanisms. In this study, we address the question of which mechanisms compositions can be considered appropriate for firm's analytical capabilities.

The dearth of information is the cause of uncertainty (Galbraith 1977). To mitigate uncertainty, firms need to have access to more information and also have the ability to processes such information. To address the increased need for information, firm's implement mechanisms and IP capability to enhance the information flow and thereby ameliorate uncertainty. For instance, mechanism such as information exchange with partners can increase information flow (e.g., Eisenhardt and Martin 2000; Malhotra et al. 2007; Overby et al. 2006). Similarly, organizations may implement IT-enabled business processes to increase the information processing capabilities, improve information flow and reduce uncertainty within organizations (e.g., Barua et al. 2004; Im and Rai 2014; Lee et al. 2008; Ross et al. 2006). The theory also suggests that amount of information and richness of information are two aspects essential to addressing task uncertainty (Daft and Lengel 1986).

Uncertainties

IPT posits that firms exist to resolve uncertainty (Daft and Lengel 1986). IPT conceptualizes uncertainty as the gap between the amount of information required to complete a task and the amount of information possessed by the organization (Premkumar et al. 2005). Organizations mitigate uncertainty using structural mechanisms that increase the flow of information and improve information processing capabilities (Bensaou and Venkatraman 1998). The amount and type of uncertainty vary across the organization. Since addressing uncertainty involves increasing information flow and information processing capabilities, organizations will

adopt numerous modes of coordination mechanisms. As highlighted by IPT, organizations need

to match the appropriate mode(s) of coordination with its particular uncertainties (Galbraith

1977). In the healthcare context, two types of uncertainty–process uncertainties and relationship

uncertainties–have significant implications on healthcare outcome. Process related uncertainties

arise out of the complex interconnected clinical and diagnostic processes (Lanham et al. 2012;

Vest et al. 2010), whereas, relationship uncertainties arises out of the inter-organizational

relationships (e.g., hospitals, insurance, testing laboratory) (Del Fiol et al. 2014; Unertl et al.

2014; Yaraghi et al. 2015). One of the key mechanisms through which healthcare organizations

enhance information processing capabilities to address process uncertainties is through the use of

IT-enabled business processes and clinical information standards (Ash and Bates 2005; Ford et

al. 2009; Rao et al. 2011). Simultaneously, to mitigate relationship uncertainties, organizations

engage in collaborative information exchanges through inter-organizational systems–e.g., health

information exchanges (Cross et al. 2015; Vest et al. 2014).

Process Uncertainties

The complexity of healthcare delivery systems, coupled with the unpredictable

trajectories of illness, is characterized by high level of uncertainty (Lanham et al. 2012). For

instance, uncertainty can be associated with making a clinical diagnosis, selecting laboratory

procedures, observing diagnostic outcomes, assessing cure probabilities, etc. Uncertainty is

compounded by the fact that all the clinical and diagnostic tasks are highly interdependent,

further amplifying uncertainty (Tang et al. 2006; Vest et al. 2015). Healthcare organizations are

typically formed as a collection of subunits having interlinked processes (Ancker et al. 2012). All

these subunits have a high degree of interdependence. In an environment of high

interdependence, healthcare task completion involves the exchange of information (McCann and

Ferry 1979). Given the high level of process interdependence, planning and adjustment are hard to achieve. While low interdependence can be addressed using standard operating procedures, high level of interdependence requires the need for common formalized language to enable the exchange of information among the processes (Thompson 1967; Malone and Crowston 1994).

Specifically, healthcare process integration can be hampered by fragmented IT which constrains information flows and process coordination (e.g., Barua et al. 2004). In contrast, integrated business processes that are characterized by common data standards enable the flow of information and coordination of activities within and across the organizational boundaries (Bala and Venkatesh 2007; Broadbent et al. 1999; Rai et al. 2006). A well-integrated process platform is much more than individual process components, and it requires formalized rules for the integration of data, applications, and processes to enhance real-time connectivity between processes (Ross 2003; Weill and Broadbent 1998; Ross et al. 2006). In such situations, firms will adopt digitally enabled process capabilities (e.g., EHR) that can leverage common information standards to exchange information. Firms will use clinical information standards (CIS) to enhance interoperability (Dolin et al. 2006; Kawamoto et al. 2013; McClay et al. 2015). By doing so, hospitals will be better able to manage task interdependencies and increase the information flow and ameliorate uncertainties associated with clinical and diagnostic processes.

Relationship Uncertainties

A significant source of uncertainty is associated with firm's relationship with other organizations (Premkumar et al. 2005; Bensaou and Venkatraman 1998; Gosain et al. 2004). Specifically, in the healthcare sector, hospitals frequently need to store, retrieve and share information (e.g., patient records) with laboratories, other hospitals, and specialized clinics. This includes vital patient information essential to making informed clinical and diagnostic decision.

Hospitals frequently acquire external information and combine it with internal information to enhance health care outcomes (Vest et al. 2009; Unertl et al. 2012).

Given the critical nature of patient data, interlinked healthcare processes require that hospitals share information that is of high quality–i.e., relevance, timeliness, completeness. This requires frequent exchanges of information that is highly time-specific and caters to the information need of the hospital. Such inter-organizational relationship requires a significant level of adjustment between partnering hospitals to support the relationship (Del Foil et al. 2014). For example, the smooth transaction of documents requires explicit or implicit agreement on standard specifications for information exchange formats, data repositories, and process interfaces between interacting healthcare institutions. Furthermore, this requires healthcare partners to agree on the syntax, semantics and pragmatic aspects of the document that are to be exchanged for the particular process being coordinated (Del Foil et al. 2014). Lack of such document exchange standards means that the transactions are idiosyncratic to each relationship. For example, a hospital may use different information reporting standards. The idiosyncratic relationship, therefore, tends to contribute to greater uncertainty. To address the uncertainty associated with relationships, hospitals are increasingly using collaborative information exchange platforms (e.g., health information exchange) (Philips et al. 2014; Vest et al. 2015). These platforms play a significant role in structuring the transactional relationship between hospital partners by reducing the extent to which clinical documents exchanges are personalized.

RESEARCH MODEL AND HYPOTHESIS DEVELOPMENT

The research model draws on the information processing theory (Galbraith 1977). In the context of this study, we define *analytical capability* as healthcare organization's ability to leverage business analytic tools (e.g., querying, online analytical processing, dashboards,

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reporting, data mining) to gain new insights related to healthcare performance, process

effectiveness, and clinical care. *CIE* refers to the extent to which a hospital is involved in

healthcare information exchange across organizational boundaries. *Extent of EHR use* refers to

the extent to which EHR systems are operational in a given hospital's clinical and patient care

workflow; *CIS* refers to the ability of EHRs to exchange, integrated, share and retrieve clinical

information across systems using standardized communication and messaging protocol. The

present research asks the following research question: how does different types of information

processing capabilities –independently or jointly-impact analytical capabilities? The conceptual

model is described in figure (1). Construct definitions–i.e., *Extent of EHR use, CIS, CIE,*

Analytical Capability- and literature support for each construct in this study are summarized in

Table 1.

Table 1	
Variable	**Conceptual Definition**
Extent of EHR use	The extent to which EHR systems are operational in a given hospital's clinical and patient care workflow (adapted from Gardner et al. 2015)
Clinical Information Standards(CIS)	Reflects the ability of health IT to exchange, integrate, share and retrieve clinical data across various systems using standardized communication and messaging protocol (adapted from HL7 International)
Collaborative Information Exchange (CIE)	The extent to which a hospital is involved in healthcare information exchange across organizational boundaries (adapted from Malhotra et al. 2007)
Analytical Capability	Healthcare organization's ability to leverage business analytic tools (e.g., querying, online analytical processing, dashboards, reporting, data mining) to gain new insights related to healthcare performance, process effectiveness, and clinical care.

The specific measures employed for each construct are detailed in the method section.

Dependent variable measures for analytical capability are documented in Appendix A. The

hospital organization serves as the unit of analysis for this study. The remainder of the section

develops the research hypotheses in three steps in relation to the outcome variable: (1) the

relationship with Extend of EHR use, (2) the relationship with the CIE and CIE, and (3) the

relationships between Extent of EHR use and the two (i.e., CIE and CIS) information processing

mechanisms.
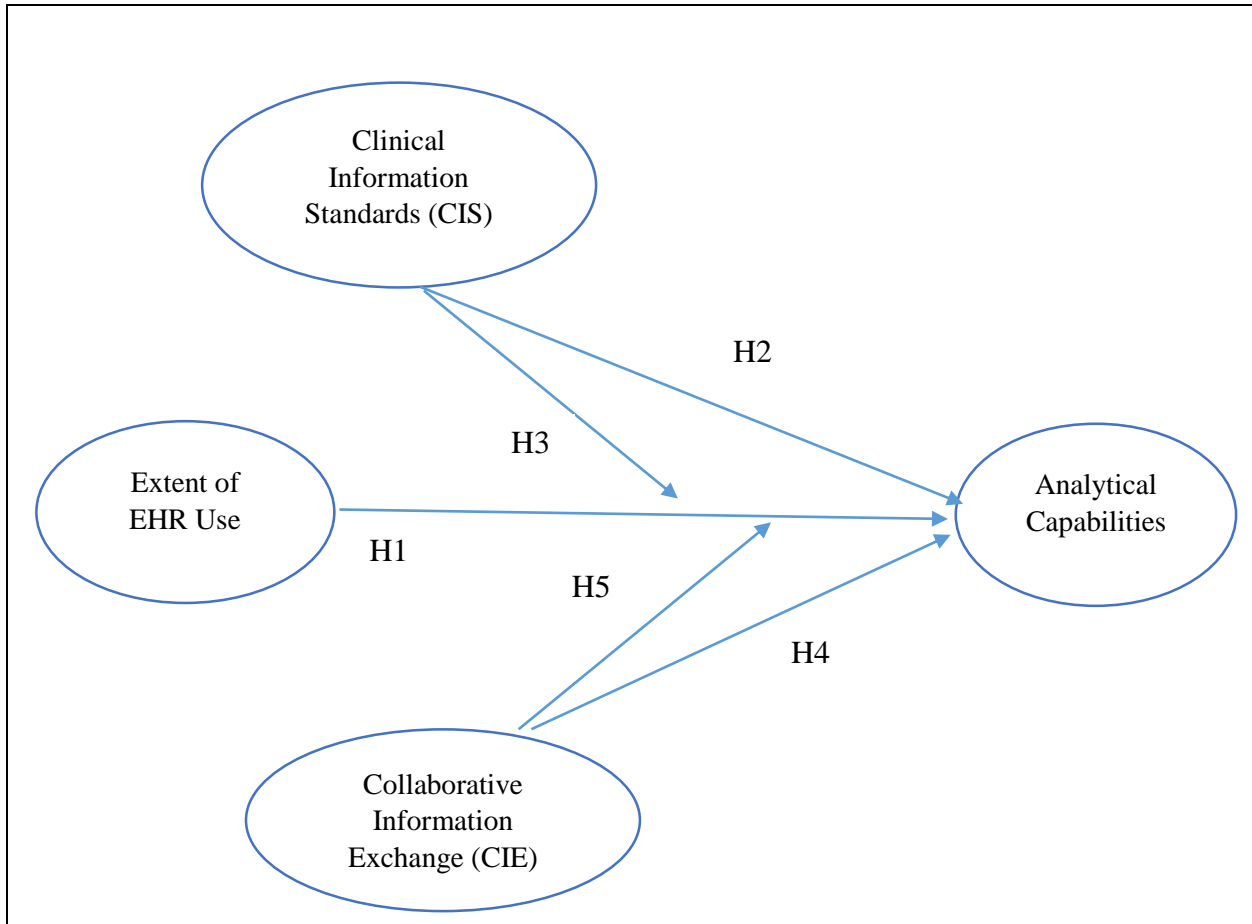
Figure 1: Research Model

While HIT is designed to exchange information across the healthcare workflow,

interdependence among unit's systems makes it a challenge to leverage BA capabilities. EHRs

ameliorate this disadvantage by automating and streamlining the clinician workflow. For

example, the EHRs can generate complete records of each clinician patient encounter.

Simultaneously, these can be accomplished directly or indirectly via multiple healthcare

application interfaces–e.g., evidence-based systems, reporting, and quality management, etc.

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Clinical data derived from EHRs contains longitudinal data of patient captured over time, with detailed records of patients' condition, medication, treatments, and responses related to an individual's evolving health status. The tremendous volume of clinical data, coupled with the complexity of the data set, makes it challenging to derive clinical and diagnostic patient care insights. Correct relevant clinical and diagnostic decisions based on a large volume of internal and external data is only possible with BA capabilities that can potential leverage the analysis of granular level healthcare data.

By providing a standardized system, the extent of EHR use becomes a key coordination mechanism that increases the ability to leverage the granular level data towards BA insights. Consequently, this enhances the ability of the hospital to manage clinical information purposefully. Extent of EHR use can lead to combination and recombination of patterns of clinical actions (e.g., Pentland and Feldman 2008) to create consistency in extracting clinical information in order to be leverage using BA capabilities (Ozdas et al. 2006). For example, CPOE can increase the clarity and consistency of prescription information entered by medical practitioners. Similarly, systems like clinical decision support systems (CDSS) reduce uncertainty and ambiguity by providing a mechanism to filter, organize data in a way that can support healthcare decision-making through data analysis (Jasper et al. 2011; Queenan et al. 2011).

Based on IPT, the extent of EHR use reflects the hospital's ability to create, gather, store, manage, and disseminate clinical information across the clinical workflow–i.e., which includes within and beyond the organizational boundary. Thus the presence of EHRs increases the flow of information across the hospital. High level of EHR use suggests hospital's increased capacity to manage a variety of information associated with the healthcare system (Kuperman and Gibson

2003). EHRs facilitate implementation of digitized clinical processes, as a result of which EHR use has been known to increase inter-unit interdependence (e.g., Ash and Bates 2005; Linder et al. 2011; Middleton et al. 2005). Thus, by increasing information processing capability, EHR use increases clinical information flow in real time. Since the information feed of business analytics relies on access to reliable, accurate, and consistent information, increased EHR use will positively influence analytical capabilities. Therefore, we argue:

H1: *Electronic Health Record (EHR) use will positively impact analytical capabilities.*

CIS plays a prominent role in improving the reliability, consistency, and accuracy of healthcare data (Harris et al. 2014; Morena-Conde et al. 2015; Richesson and Nadkarni 2011). CIS facilitate the integration of diverse systems across the healthcare–i.e., legacy as well as contemporary. CIS standardizes the data interfaces or data feed to other information systems. This increases the ease with which clinical data can span system boundaries. System boundaries arise due to the variation in information (amount and/or type), the degree of dependence of the information, and the degree of shared understanding between the systems involved. CIS create a boundary spanning mechanism by increasing the syntactic interoperability between the interdependent systems (Richesson and Nadkarni 2011). This ensures all the systems understand the structure and provenance of information. By providing a machine readable format with pre-defined structure, CIS increases the semantic interoperability–i.e., systems can understand the semantics of information request and those of information sources. Increased coordination among systems due to boundary spanning mechanism requires syntactic and semantic interoperability. Spanning these boundaries increases the efficiency in the flow of information across the healthcare environment. The idea of a syntactic and semantic boundary is rooted in the information processing view (Lawrence and Lorsch 1967; Galbraith 1977; Tushman and Nadler

1978). Increased coordination among systems due to boundary spanning mechanism requires syntactic and semantic interoperability. Spanning these boundaries increases the efficiency in the flow of information.

CIS establish a shared language between the systems, thereby acts as the glue that connects the organizational systems and provides a conduit to exchange information by shared, pre-establish and pre-defined meanings of information. This is critically important for the organizations to leverage analytics in building predictive models areas of performance, clinical and process improvements. For example, one of the major hindrances that characterize hospital performance is medical claims processing. Anomalies of medical claims associated with costs (e.g., medical fees and charges, accommodation costs, test costs) or care quality (e.g., the length of stay, mortality, readmission, unexplained infections, etc.) are caused by inefficiencies in the healthcare system (IOM 2012). By having access to rich real-time information, hospitals can build analytical models that can detect and investigate anomalies associated with health claims (Caban and Gotz 2015; Voss et al. 2015). Because data arrives in predefined formats from multiple sources, it becomes easier to select key data elements needed to build analytical models accurately. Thus, we can argue that CIS is critical to build better analytical capabilities. Therefore, we argue that:

H2: *Greater use of clinical information standards (CIS) will positively impact analytical capabilities.*

Hospitals operate in a complex and dynamic environment with a significant amount of uncertainty associated with health care processes (Lanham et al. 2014; Nembhard and Tucker 2011). Hospitals decompose healthcare workflow processes into atomic level fine-grained units of functionality to address the complexity. These processes are combined and recombined to

execute the health care tasks. According to IPT, to mitigate the uncertainty healthcare organizations have to increase the information processing capability. Although the use of EHRs reflects the information processing capabilities, uncertainty arises due to lack of data integration and interoperability (e.g., D'Amore et al. 2014; Tang et al. 2006). Specifically, uncertainty is associated with lack of standardized data vocabularies, structure, open and accessible programming interfaces. The presence of CIS mitigates the uncertainty related to integrating a wide variety of data formats arising from the use of EHR.

CIS are open standards that allow for greater flexibility in establishing increased information flow between systems (Zhu et al. 2006) by providing a predefined data structure. As a result of which, CIS improves conformance quality of the data resulting in high information quality. Increased information flow due to real-time operational data from various sources enables real-time analysis and decision support to provide the relevant insights for decision making. High interconnections between the processes mean high visibility of the real-time performance of various processes and integration between processes. We can argue that data integration across multiple EHR reduces uncertainty by increasing real-time information flow. However, the biggest contribution to building analytical capabilities is associated with creating an analytics ecosystem that captures electronic granular level data from patients, clinicians, and digital assets. In fact, EHR provides the critical mechanism to capture the pieces of data that collectively form information needed to build analytical models. Although EHR generates staggering amount of clinical data, CIS provides meaning to these data by providing a predefined format. Due to this, BA can effectively combine longitudinal clinical data with patient-generated health data in developing actionable insights to understanding patient's clinical and diagnostic progression better. Therefore, we argue that:

H3: *Greater use of clinical information standards (CIS) will positively moderate EHR use and analytical capabilities*

The complex and the interdependent nature of the healthcare environment requires hospitals to exchange patient related clinical data across organizational boundaries. Relational uncertainty is a key driver that necessitates standardized the collaborative exchange of clinical information (Lanham et al. 2014). The idiosyncratic nature of the exchange transactions requires predefined messaging formats, process interfaces and frameworks for inter-organizational system integration. In other words, hospitals require capabilities that can seamlessly interconnect clinical process linkages (Philips et al. 2014; Terry et al. 2013). Given the highly distributed nature of healthcare processes, collaborative information exchange platforms connect these distributed processes that span organizational boundaries by providing a conduit for the seamless flow of information. These platforms provide a structural mechanism through which healthcare organizations can automate sharing of clinical information. Healthcare organizations require rich information (e.g., lab results, patient data, and medical history) from other healthcare partners towards efficient completion of clinical and diagnostic tasks.

The distributed nature of CIE increases the ability of the hospital to analyze quality information by enhancing the flow of timely, accurate, and reliable information (Unertl et al. 2012). Such platforms increase the transactional efficiencies between partner systems across the domain through many-to-many electronic connectivity relationships between health care organizations. Consequently, partners have access to much richer information in the whole healthcare workflow. Hospitals can share a broad range of high-quality information. For example, sharing of test results between two hospitals. Thus, it is safe to argue that by increasing information flow through inter-organizational process linkages, CIE improves the quality of

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organizational data fed into the analytic systems. Thus, by using rich internal and external information, hospitals are better able to leverage analytics. Therefore, we argue that:

H4: *Hospital's participation in collaborative information exchanges positively influences analytical capabilities*

CIE acts as a centralized hub for relevant healthcare parties to share clinical information electronically using federally defined standards of continuity of care records and documents. EHRs connected through CIE can send/receive timely information–e.g., patient discharge summary, patient history, and medication history, amongst others. One of the key challenges of connecting EHRs beyond organizational boundaries is the fact that each EHR implementation is built by disparate vendors implementing certain proprietary applications. By providing a global standards of connectivity regarding information exchange, CIE makes the EHRs truly interoperable across the organizational boundaries.

CIE participation reflects hospital's ability to access timely, relevant, and accurate information in the whole healthcare domain. Furthermore, centralized nature of CIE architecture makes updated information available instantly to each stakeholder. In true sense, CIE make the EHRs interoperable across the healthcare environment–thus amplifying EHRs effect. This is consistent with the notion that various information processing mechanism are not the substitute for one another but have a complementary effect on mitigating uncertainty (Galbraith 1974). Different combination of organizational systems suggests unique choices regarding how data is generated, aggregated, transformed and disseminated for organizational task (Stock and Tatikonda 2008). Thus, CIE and EHR integrate in a complementary manner to increase the information processing capabilities of the healthcare organization.

EHR frequently need to process external information (e.g., test results, patient history) for task completion. Access to secure, reliable and timely information from CIE goes towards mitigating task uncertainty associated with the process completion. It is also essential that firms have a high level of EHR use in order to leverage external information (Hah and Bharadwaj 2012). The complementary information processing capabilities result in rich information, which is feed into business analytics systems. To this extent, CIE has been termed as 'information aggregator' for analytics systems, capable of aggregating patient level granular data from disparate systems spanning organizational boundaries (Singh et al. 2011). Thus, the participation of the hospital in these CIE result in a set of capabilities that drive inter-organization connectivity, clinical data messaging across geographic boundaries, predictive analytics, and decision support. Thus, we argue that:

H5: *EHR use is more positively related to analytical capabilities when the hospital has high level of participation in collaborative information exchange (CIE) than when the hospital has low participation.*

RESEARCH METHODS

The proposed relationships are tested using two secondary databases–*HIMSS Analytics 2013* and *AHA IT Survey 2013*- on EHR implementation within U.S. hospitals. Our use of multiple sources of data facilitates an increased degree of validity and insights that are not possible from individual data sources. We select two survey datasets from American Hospital Association's (AHA) and Healthcare Information and Management Systems Society (HIMSSS), yielding more than 5000 hospitals from 50 states. In general, AHA's dataset provides IT implementation information at more than 5232 U.S. hospitals whereas HIMSS Analytics data has profiled and updated 5168 hospital data, containing software, hardware, and infrastructure

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installed through all facilities within each hospital. HIMSS surveys chief information officers and other IT executives annually to assess the adoption status of multiple HIT applications. Examples of HIT categories include electronic medical records, financial decision support, human resources, health information management, cardiology, radiology, revenue cycle, and ambulatory. On the other hand, AHA IT survey assesses the functional use of key IT applications (e.g., EHRs).

We merged the data of the U.S. hospitals from two separate sources using the Medicare ID. The Medicare numbers are unique identifiers given to hospitals that benefit from government Medicare payments. The AHA IT Survey provides the data for dependent variable (i.e., analytical capabilities) whereas HIMSS Analytics provides the data for all the independent variables. We tested the direct as well as moderated relationship between the independent variables (i.e., Extant of EHR use, CIE, and CIS) and the dependent variable (i.e., Analytical capabilities). Our study is focused on broad hospital efforts surrounding EHR use and organizational level information processing. As such we examine how information processing mechanisms may interact and the influence analytical capabilities.

DATA VARIABLES

Extent of EHR use is measured using secondary data provided by the Healthcare Information and Management Systems Society (HIMSS) Analytics database. Specifically, we are interested in the EHR modules (Appendix Table 8) that a given hospital has adopted as live and operationalized in the healthcare workflow. To calculate the EHR use level for a given hospital, we counted the number of adopted EHRs out of eight possible EHR modules and divided the count by 8 to calculate a proportion (e.g., Angst et al. 2010; Gardner et al. 2015; Queenan et al. 2011). This coding designation is consistent with HIMSS and with coding employed by Angst et

al. (2010). To measure *collaborative information exchange* (CIE*)* used by the hospital, we count the number of exchanges in which the hospitals participate (Appendix Table 9). We count the number of CIE out of possible 18 identified in HIMSS and divide the count by 18 to calculate the proportion. CIE is operationalized as the proportion of healthcare information exchange initiatives that a given hospital is involved. HIMSS database identifies and documents 18 information exchange initiatives that hospitals are associated with. *Clinical information standards* (CIS) is measured as a binary variable (0,1) reflecting if clinical information standards are used as an interoperable technology to seamlessly connect electronic healthcare record systems. CIS is measured as a dichotomous variable based on whether or not a hospital fully and actively uses clinical information standards.

In the AHA survey data, hospitals were self-assessed on the extent to which specific functionalities associated with business analytics were used for information processing. Using the survey data, we constructed the *analytical capabilities* construct. Based on the use, we conceptualize the construct as a formative model having three dimensions: *performance analytics*, *clinical analytics*, and *process analytics*. Table 1 shows the items of the formative dimensions. Each dimension was standardized based on z-score scaling and then aggregated to form the analytical capabilities construct.

Besides the key research variables, several control variables, used in the extant literature, were included to account for potential confounding effects. For hospital-level characteristics, we calculate the age of the hospital, net operating revenue, revenue from Medicare, revenue from Medicaid, IS budget, hospital type (academic/nonacademic), and the location of the hospital. The operationalization of the variables is described in Table 1 and Table 2.

Table 1: Controls	
Variable	**Operationalization**
Age	Reflects the age of the hospital
Net Operating Revenue	Net operating revenue includes revenues associated with the primary operations of the hospitals
Revenue Medicare	Percent of Medicaid that makes up the patient revenue at the hospital
Revenue Medicaid	Percent of Medicaid that makes up the patient revenue at the hospital
IS budget	IS department operating expense as a percent of total operating expenses at the hospital
Hospital Type	If the hospital is academic or non-academic
Location	If the hospital is rural/urban

Table 2. Variables and Operationalization	
Variables	**Operationalization**
Analytical Capabilities	**Please indicate whether you have used electronic data from the EHR in your hospital to:** **Performance analytics** - Create a dashboard with measures of organizational performance - Create a dashboard with measures of unit-level performance - Create individual provider performance profiles - Generate reports to inform strategic planning **Clinical analytics** - Identify care gaps for specific patient populations. - Identify high risk patients for follow-up care using algorithm or other tools **Process analytics** - Create an approach for clinicians to query the data - Assess adherence to clinical practice guidelines - Maximize quality improvements
Extent of EHR use	The proportion of EHR operational in the hospital. HIMSS identifies 8 EHR modules that collective form the EHR system.
Clinical Information Standards (CIS)	Is HL7 transactions used to share patient data?
Collaborative Information Exchange (CIE)	The proportion of information exchange initiatives that a hospital is involved. HIMSS identifies 18 information exchange initiatives

Since our sample data used to test the hypothesized relationships is secondary data, data analysis

may be contaminated with outliers or influential observations. To detect outliers and influential

observations, we use the Cook's distance statistics (or Cook's D) (Cook 1979). It is entirely

possible that a single observation can have a disproportionate influence on the statistical analysis.

By using the Cook's distance, we test how much the predicted scores for other observations

would differ if the single observations in question were not included. The presence of any

significant difference would suggest influence on the research model. Based on the rule of

thumb, observations having the cook's distance above 1.0 were dropped from the sample[1]. After

thoroughly examining the outlier analysis, we retained 355 observations. The summary statistics

of the variables are presented in Table 3.

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[1] Test of research model without dropping observation (*n=361*) yields h1($\beta=.18$); h2 ($\beta=.11^*$); h3
($\beta=.09$); h4 ($\beta=.03$); h4 ($\beta=.17$); h5($\beta=-.09$)

Variables (N = 355)	1	2	3	4	5	6	7
1. Age	1						
2. Net Operating Revenue	.137**	1					
3. Medicare	.027	-.133**	1				
4. Medicaid	.011	.093*	-.216**	1			
5. IS Budget	.112*	.502**	-.043	.033	1		
6. Hospital Type	.076	.387**	-.037	.044	.164**	1	
7. Location	-.051	-.379**	.086	-.030	-.203**	-.138**	1
8. Extent of EHR use	.037	.144**	-.036	-.021	.085	.042	.077
9. CIS	.025	-.002	.062	-.008	.067	.031	.086
10. CIE	.015	.095*	-.081	.099*	.047	.045	.043
11. EHR Assimilation	-.071	-.090*	.022	.049	-.071	.022	.007
12. HIT Infrastructure	-.047	-.060	.015	.008	-.100*	.090*	.034
13. Analytical Capability	-.024	.382**	-.063	.002	.267**	.151**	-.139**
Mean	52.98	304.6	38.1	14.1	.04	.12	.12
SD	39.50	383.1	12.0	8.4	.07	.33	.34

Variables (N = 355)	8	9	10	11	12	13
1. Age						
2. Net Operating Revenue						
3. Medicare						
4. Medicaid						
5. IS Budget						
6. Hospital Type						
7. Location						
8. Extent of EHR use	1					
9. CIS	.199**	1				
10. CIE	.157**	.202**	1			
11. EHR Assimilation	-.313**	.033	-.002	1		
12. HIT Infrastructure	-.353**	.027	-.038	.889**	1	
13. Analytical Capability	.215**	.130**	.163**	-.045	-.033	1
Mean	.59	.55	.11	39.61	.44	.56
SD	.24	.49	.10	25.19	.27	.26

Notes: $^*p < .05$; $^{**}p < .01$; $^{***}p < .001$

RESULTS

We estimate the following data model:

Ln (*Analytical capabilities*) = β_0 + β_1 Ln(*Age*) + β_2 Ln (*Net Operating Revenue*) + β_3

Ln(*Medicare*) + β_4 Ln(*Medicaid*) + β_5 Ln (*IS Budget*) + β_6 (*Hospital type*) + β_7 (*Location*) + β_8

(*Extent of EHR use*) + β₉ (*CIS*) + β₁₀(*CIE*) + β₁₁ (*Extent of EHR use * CIS*) + β₁₂ (*Extent of EHR use * CIE*) + e

We tested the hypothesized relationships among the constructs using OLS regression analysis. To ensure that we have a consistent estimator, we tested for any potential violations of least square assumptions–i.e., normality, linearity, independence, and homoscedasticity. The combined effects of a biased estimator due to the violation may have strong consequences while deriving inferences because of the aggregation of the effect of a large number of variables (Greene 2008). A combination of visual plots and statistical techniques was used to test the key least square assumptions. To test for any violations of normality, we used the Shapiro-Wilk test. The result is not significant (*p-value* > *.05*), thus suggesting the data is from a normally distributed population. Testing the standardized residual against the frequency suggests the variances is normally distributed. A symmetric bell-shaped curve, evenly distributed around zero, indicated that the normality assumption is not violated. For testing violation of the assumption of independence, we used the Durbin-Watson test. The residual tests of the variables suggest that the variables are independent, and the model is correctly specified. The Durbin-Watson test result is 2.1. Based on the rule of thumb, the residuals are not correlated if the Durbin-Watson statistic is approximately 2, and within an acceptable range of 1.50–2.50 (Greene 2008). To test the assumption of homoscedasticity, we used the Breusch-Pagan test. Results of the tests suggest lack of any violations in homoscedasticity (*p-value* > *.05*). We also tested for homoscedasticity and did not find any violations related to equal variance. Overall, we did not find any evidence of OLS assumption violation.

Table 4 shows the results of the tested models. In the first hypothesis, we proposed a relationship between the *extent of EHR use* and *analytical capabilities*. The coefficient is positive

and is statistically significant ($\beta=.133^{**}$) suggesting that extent of EHR use in the hospital business process has a positive association with hospital's analytical capabilities. Thus we found support for H1. In the second hypothesis, we argued that use of clinical information standards could potentially influence hospital's analytical capabilities. Our results support our assertion ($\beta=.085^{*}$), thus supporting H2. In the third hypothesis, we argued that the interaction effect of the extent of EHR use and clinical information standard would positively influence analytical capabilities.

We created the interaction term by multiplying the variables (Kenny 2004) and the resultant standardized coefficient measures how the effect of the extent of EHR use and clinical information standards varies. The interaction between the two variables is not significant ($\beta=.026$). Thus our assertion that of the interaction effect is not supported. In the fourth hypothesis, we proposed a relationship between collaborative information exchange and analytical capabilities. The coefficient is positive and is statistically significant ($\beta=.099^{*}$) suggesting that hospital's participation in collaborative information exchange has a significant effect on analytical capabilities. Thus we found support for H4. Finally, in the fifth hypothesis, we proposed an interaction effect of the extent of EHR use and collaborative information exchange on analytical capabilities. Our results suggest no significant effect of the interactions on analytical capabilities. Thus we did not find any support for H5 ($\beta=-.013$). Summary of the hypothesized relations and its support are shown in Table 5.

Table 4. Predicting Analytical Capabilities (OLS)							
	Controls		Main Effects		Interaction Effects		
R²	.16		.20		.20		
ΔR²			.04		.00		
	β	**SE**	**β**	**SE**	**β**	**SE**	**VIF**
Age	-.082	.035	-.086*	.034	-.085*	.034	1.028
Net Operating Revenue	.341***	.030	.305***	.029	.302***	.030	1.803
Revenue Medicare	-.019	.048	-.014	.048	-.017	.048	1.108
Revenue Medicaid	-.037	.053	-.039	.052	-.041	.052	1.080
IS Budget	.105*	.027	.095*	.026	.095*	.026	1.356
Hospital Type	.010	.095	.009	.093	.009	.093	1.181
Location	.009	.096	-.029	.096	-.034	.097	1.238
Extent of EHR use			.135**	.121	.133**	.122	1.112
Clinical Information Standards (CIS)			.083*	.059	.085*	.059	1.101
Collaborative Information Exchange (CIE)			.096*	.292	.099*	.307	1.193
Extent of EHR Use × CIS					.026	.245	1.070
Extent of EHR Use × CIE					-.013	1.306	1.190

Notes: $^*p < .05$; $^{**}p < .01$; $^{***}p < .001$

Table 5. Summary of Hypothesis Testing		
Hypothesis	**Description**	**Support?**
H1	Extent of EHR Use -> Analytical Capabilities	Yes
H2	Clinical Information Standards - > Analytical Capabilities	Yes
H3	Extent of EHR Use × Clinical Information Standards - > Analytical Capabilities	No
H4	Collaborative Information Exchange - > Analytical Capabilities	Yes
H5	Extent of EHR Use × Collaborative Information Exchange - > Analytical Capabilities	No

To further test for the robustness of interaction effect, we conducted a subsample analysis of the moderation effect. We tested for the moderation effect in two subsamples, split on the basis of the mean of the observations associated with analytical capabilities. Before testing for the moderation effect in subsamples, we test for significant association in the difference of observable characteristics between the moderator variables (i.e., CIS and CIS) and analytical capabilities. Using Chi-squared test, we tested for the goodness of fit between observed values and those expected theoretically in the research model. In other words, we test if there is a

significant difference between expected frequencies and the observed frequencies. Do the hospitals with CIS and hospitals without CIS differ significantly and, if so, is it due to sampling variation or is it due to a real difference.

While CIS is a categorical variable, CIE and analytical capability are not. To create categorical values, we dichotomize analytical capability and CIE based on the mean value of observations. Observations with values above the mean are coded as 1 and values below the mean are coded as 0. Dichotomizing analytical capability yields a sample with 157 observations coded as 1 and 198 observations coded as 0. Similarly, dichotomizing CIE yields a sample with 165 observations coded as 1 and 190 observations coded as 0. First, we asked if hospitals with CIS differ significantly from those hospitals not having CIS. The results suggest that there is statistically significant association between CIS and analytical capability ($\chi^2 = 5.25; p < .05; df =1$). That is, both categories (CIS =1 and CIS =0) have significant differences when it comes to analytical capability. Second, we asked if hospitals with high CIE differ significantly from those with low CIE when it comes to analytical capability. The tests suggest that there is a statistically significant association between CIE and analytical capability ($\chi^2 = 4.47; p < .05; df =1$).

Having established the statistical significance of the moderator variables (i.e., CIS and CIE) to analytical capability, we tested for the moderation effects using two subsamples. The subsamples were divided into two groups by using the mean value of the observation as the split criteria. The first subsample, high analytical capability (N=157), contained observations with analytical capability above the mean value and the second subsample, low analytical capability (N=198), contained observations with analytical capability below the mean. In the case of the subsample with high analytical capability, the results suggest no interaction effects of moderator variables (CIS ($\beta=.15$) and CIE ($\beta=-.19$)) on the relationship between the *extent of EHR use* and

analytical capability. In case of the subsample with low analytical capability, the results suggest no interaction effects of moderators (CIS (β=.*19*) and CIE (β=-.*13*)) on the relationship between the *extent of EHR use* and *analytical capability*. In conclusion, we did not find any interaction effect in the subsamples test. Furthermore, we conducted multiple robustness checks to examine the sensitivity of the results obtained from the analysis.

ROBUSTNESS CHECK - MULTICOLLINEARITY

We tested the presence of multi-collinearity in our theoretical model. Specifically, we tested if more than two theoretical variables are linear combinations of one another. In such circumstances, perfect linear relationships among these predictors would suggests that the least square estimates cannot be uniquely computed. The threat of multi-collinearity suggests that as the degree of multi-collinearity increases, least squares estimates become unstable resulting in inflated standard errors. In order to test for such threats, we use the Variance inflation factor (VIF). VIF detects if two or more variables are linear combination of each other. A VIF value above 10 suggests the possibility of multi-collinearity among the predictors (Goldberger 1991). In case of the current regression model, the VIFs range between 1.06 and 7.33, which is well below the cutoff value of 10. Any predictor with the VIF value above 10 would merit further investigation to address the threat of multi-collinearity. Thus, our test suggests lack of any threat of multi-collinearity among the predictors in the model.

ROBUSTNESS CHECK - COMMON METHOD BIAS

There is a possibility that method variance may have inflated the observed theoretical relationships between principal constructs. To test the threat of common methods bias, we performed two tests: (a) Harman's Single factor test (Podsakoff et al. 2003), and (b) Lindell and Whitney's test. First, to test for Harman's one factor, all the principal constructs were entered

into a factor analysis (Podsakoff and Organ 1986). Common method bias exists if there emerges a single factor accounting for a significant portion of variance among all the constructs. Our tests suggest no such single component exists that explained for any excessive proportion of variance. Each of our theoretical constructs explained roughly similar variance, ranging between 3.8% and 14.5%, indicating a lack of any extreme threat from common method biases. The factor accounting for the largest proportion of variance was 14.5%, below the cutoff rule of 18% (Podsakoff 2000).

Second, threat assessment of CMB was tested using Lindell and Whitney's (2001) marker variable test. The method employs a theoretically unrelated (i.e., marker) variable to adjust the correlations among the model's principal constructs. Since there exists no relationship between the marker variable and the theoretically justified relationships, high correlations would support the assertions that CMV exists (e.g., Malhotra et al. 2006). To ensure robustness of the test, we used two marker variables (CPOE and CDSS) that lacked theoretical connections with the existing model. High correlations among the markers and the principal constructs would suggest common method biases existence. Our tests suggest that the average correlations for the marker variables were: CPOE (*r= 0.084, p-value = 0.85*) and the CDSS (*r = 0.166, p-value = .20*) were non-significant, reflecting lack of evidence of threats of common method bias.

ROBUSTNESS CHECK FOR ENDOGENEITY

A primary concern in the use of secondary data is potential endogeneity between analytical capabilities and Extent of EHR use. It is entirely possible that hospitals having a high level of analytical capabilities may necessitate a need for greater use of digitized IT-enabled business process (i.e., EHRs). To ensure robustness we tested for any existence of endogeneity

using two methods: (1) two state least squares (2sls) using instrumental variables (Woolridge 2002), and (2) propensity score matching (Rosenbaum 1999).

TWO-STAGE LEAST SQUARE

To conduct the 2SLS, we identified two exogenous instrumental variables (IV)– *EHR assimilation* and *HIT Infrastructure*- that are strongly correlated with the potential endogenous regressor (Greene 2008). And to do so, we followed Greene's (2008) steps in identifying IVs using some key conditions. The IVs are observed variables that must satisfy several conditions – (a) errors are uncorrelated, (b) variable should be endogenous, (c) observed variable must be correlated with the prediction variables, and (d) at least as many IVs as there are variables that we intend to replace. Commonly used instruments for the *extent of EHR use* are not available to us. Due to this lack of available instruments, we followed prior work and used variables that provide an approximation (i.e. *EHR assimilation*) of the functionality provided by EHR (e.g., Villas-Boas and Winer 1999). Based on the conditions, we identified two IVs–*EHR assimilation* and *HIT infrastructure*–as variables to be used for the two stage least square analysis. We tested for the endogenous nature of the two variable using correlation measures. Based on the recommendations, the two variables have to be moderately correlated with the endogenous variables in order to satisfy the conditions of the selections of IVs. Our correlation measures in relationship to the endogenous variables reflects moderate correlations between the IVs and the endogenous variable.

EHR assimilation is defined as "*the extent to which EHR use is integrated with the care delivery process and becomes routinized in the activities associated with clinical process*" (see Mishra et al. 2012). Based on the health IT literature, we identified *EHR assimilation* as a four item factor consisting of key EHR functionality–i.e., electronic notes and documentation,

prescription management, laboratory management and medication management (Mishra et al. 2012). We used the AHA IT survey's documented EHR functionalities to operationalize the construct. *HIT infrastructure* is defined as the extent to which available information technology are live and operational in a given hospital (Gardner et al. 2015; Angst et al. 2010). *HIT infrastructure* reflects the hospitals ability to gather, store, manage, and share patient information (e.g., admissions, discharges, billing information). HIT infrastructure is measure using the secondary data from HIMSS Analytics 2013. The measure reflects the aggregate of healthcare IT used towards clinical and administrative processes. HIMSS Analytics identifies a total of 58 possible technologies. HIT infrastructure is measured as the proportion of IT that a given hospital has operationalized in the workflow. Table 4 shows the results of the endogeneity test. Results suggest that one of the instrumental variable –i.e., HIT infrastructure ($\beta = -.316^{***}$)- has a significant effect on analytical capabilities. Results from the test imply the existence of some reverse causation suggesting that high level of analytical capabilities may be associated with greater extent of EHR use. Thus, the analysis suggests that EHR use may be associated with adverse selection in case of some hospitals.

PROPENSITY SCORE MATCHING

Non-experimental data often fail to meet the key assumption of random assignment. Unlike experimental data, it is not possible to randomly assign treatment and control groups. As a consequence, the data may potentially be affected by observed and unobserved characteristics of the subject. Thus, direct comparisons of mean outcomes may possibly overestimate or underestimate the true causal effect. To address this selection bias, we use a matching technique based on calculated propensity scores (Rosenbaum 1999). Furthermore, we conduct a sensitivity

analysis to assess the severity of the selection bias (Rosenbuam 2002; Rosenbaum and Rubin 1983).

In the present case, the treatment is CIS, outcome of interests is analytical capabilities and independent variables (EHRuse and CIE) as covariates. To assess the average treatment effect, we make some assumptions related to the observed data–i.e., the presence of selection bias is a consequence of correlation between subject's characteristics and the treatment status. To generate the propensity score, we stratified the observations into two groups–i.e., groups having CIS (CIS = 0; N=165) and a group not having CIS (CIS=1; N=196). We use a kernel matching probit estimator (Heckman et al. 1998) as the estimation method to calculate the propensity model. The calculated propensity score for EHR use was 0.8 (*p-value* < *.05*) and CIE was 2.66 (*p-value* < *.05*). The results suggest that the selection model is significant with a model with no explanatory variable. Thus, hospitals differ significantly from those with a model with no explanatory variables. This answers the question: - do all hospitals benefit equally if they acquire CIS?

To further ensure robustness of the result, we also conducted a sensitivity analysis to check the sensitivity of the causal effect to potential violations (see Rosenbaum 1999). The sensitivity analysis reflects the magnitude of biases present that can potentially alter the inference derived from the analysis. To this extent, we used the Wilcoxon Sign-Rank tests for the average treatment effect on treated (i.e., those who have CIS). Results suggest a threshold factor of 170% ($\gamma = 1.7^{**}$). This means that we are more likely to find unobserved selection bias if the difference between treatment and controls exceeds 170% in terms of unobserved characteristics. In other words, the sensitivity analysis informs us that the estimated causal effects may have

been overestimated or underestimated if we believe that hospitals with CIS are 170% more likely than comparative hospitals without CIS to be endowed with any unobserved factor.

Table 7. Endogeneity Test (2SLS)				
	OLS		**2SLS**	
R^2	.20		.19	
ΔR^2			.01	
	β	**SE**	**β**	**SE**
Age	-.085[*]	.034	-.058[*]	.034
Net Operating Revenue	.302[***]	.030	.148[***]	.031
Revenue Medicare	-.017	.048	-.022	.049
Revenue Medicaid	-.041	.052	-.048	.053
IS Budget	.095[*]	.026	.044[*]	.026
Hospital Type	.009	.093	.010	.093
Location	-.034	.097	-.035	.101
Extent of EHR use	.133[**]	.122	.028	.339
Clinical Information Standards (CIS)	.085[*]	.059	.124[*]	.065
Collaborative Information Exchange (CIE)	.099[*]	.307	.674[*]	.326
Extent of EHR Use × CIS	.026	.245	.147	.247
Extent of EHR Use × CIE	-.013	1.306	-.669	1.370
Instrument Variables				
EHR Assimilation			7.36	.001
HIT Infrastructure			-.316[***]	.097
Notes: [*]p < .05; [**]p < .01; [***]p < .001				

ROBUSTNESS CHECK: ALTERNATE MEDIATION MODEL

Although we proposed a moderated model, where CIS and CIE moderate the relationship between the extent of EHR use and analytical capabilities, it is quite possible that there exists a mediating relationship among the principal constructs. Therefore, to ensure robustness of results we also tested for an alternate model specification to determine whether CIS and CIE mediate the impact of the extent of EHR use on analytical capability. To test for the existence of any mediated relationships, we conducted the Barron and Kenny's (1986) mediation test and Sobel's (1982) standard error test. First, we tested for any significant effect of extent of EHR use on CIS. The results suggest a lack of support for any significant relationship ($\beta = .25$). Similarly, we also tested for any significant effect of extent of EHR use on CIE. The results suggest a lack of

support for any significant relationship ($\beta = .18$). Since we did not find any significant relationship between the *extent of EHR use*, *CIE* and *CIS*, we, therefore, rule out any mediating relationship with the model. To ensure further robustness of the initial mediation test, we conducted the Sobel's (1982) standard errors test. Similar to previous results, we find a lack of any significant effect of CIS or CIE. The results reflect a lack of any mediational relationship between the theoretical constructs. Thus the empirical results, along with our theoretical arguments provides strong support for the espoused moderation model and lack of support for the mediation model.

ROBUSTNESS CHECK: Uncaptured nonlinearity

We test if any nonlinear combinations of the explanatory variables have any power in explaining the response variable (i.e., analytical capability), then the model is not specified. In order to test for any uncaptured nonlinearity patterns in our data, we conducted the Ramsey RESET test. The results (*F = .48; p-value > .5*) does not support any evidence of misspecification in our model.

<div align="center">

DISCUSSION

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The results of the study provide empirical evidence that extent to which hospitals integrate core IT-enabled business processes (i.e., EHRs) can serve as an efficient mechanism for increasing information processing capability and improving information flow leading to direct improvements in analytical capability (h1). As hospitals integrate more modules in the healthcare workflow, an increase in information processing capability will improve hospital's ability to leverage analytics. The significant relationships between CIS and analytical capability (h2) suggest that integration of healthcare systems is one of the most effective mechanisms to improve analytical capability. Given the recent survey of hospitals on HIT systems, more than 50% of the major healthcare organizations continue to rely heavily on older mainframes and

legacy based system (Becker et al. 2015). By providing standardized interfaces, CIS strengthens process coordination mechanism to enhance information flow among digitized processes, thereby improving analytical capability.

The significant relationships between CIE and analytical capability (h4) suggest that robust analytical capability is not merely factor specific to the organization but spans the organizational boundaries. The distributed nature of healthcare process necessitates platforms that can connect processes that transcend organizational boundaries. CIE increase the transactional efficiencies between partnering hospitals and provides a conduit for the seamless flow of timely, accurate, and reliable information. The network of inter-organizational relationships thus become a source of critical organizational data, bring rich real-time data critical to making evidence-based decisions. We do not, however, find a significant moderating effect of CIE and CIS (h3 and h5) on the relationship between the extent of EHR use and analytical capabilities. A plausible reason could be that CIS standards are still evolving and have not been fully defined for EHRs. Similarly, even though CIE goal is to increase the exchange of information through standardized inter-organizational processes, hospitals are yet to integrate fully at a scale where benefits are evident.

LIMITATIONS AND FUTURE RESEARCH

As with all papers, the current study has limitations. One of the key limitation is the cross-sectional nature of the data. The paper tests the theoretical relationships assuming health care technology integration as a static entity. By doing so, we ignore the artifact itself. The richness and the complexity of the theoretical relationship depend on observing the emergence of the phenomenon of interest (i.e., analytical capability). While integration of key IT capabilities into the organizational ecosystem evolves over time, our cross-sectional data fails to capture that

emergence phenomenon. Another limitation of the paper is the use of a coarse measure of EHR operationalization. EHRs are digitized IT-enabled healthcare process templates, and each hospital uses distinct sets of functionalities by its contextualized needs influenced by various organizational factors–i.e., use patterns, power, politics, etc. We did not specifically investigate the extent of using these particular EHR functionalities. This is primarily because our current data is insufficient to provide details about such user patterns. Capturing specific use of EHR feature can provide insight about inflection points that may have a disproportionate influence on analytical capability.

Although we investigated the extent of information processing capabilities on analytical capabilities, future research should focus on other distinct information processing mechanism in the health care context and its implications on firm's analytical capabilities. For example, hospitals are increasingly adopting distributed IT architectures (e.g., web services/service oriented architecture) as ICT design strategy. While analytics are being built over these new generations of computing architecture, what roles do they play in building and leveraging analytical capability? Simultaneously, there is also need to examine other specific information processing mechanisms (e.g., enterprise resource planning) and the complementarity effect achieved on performance metrics (e.g., quality of care, mortality, patient satisfaction). Future research should also explore different ways that stakeholders (e.g., physicians, nurses, paraprofessionals) process and utilize the information and its connections to organizational value appropriation. Future research can look into organizational decision environment–i.e., policy makers, roles, decision hierarchies- and its impact on analytical capability.

Furthermore, this paper highlights the need for more exploration of the analytical capability construct. Future research should tease out the multi-dimensional nature of this

construct. This can potentially yield a fertile area of investigation associated with targeted interventions of analytical capabilities and its consequences. Additional studies can be done to examine the evolution of analytical capabilities spanning organizational boundaries (e.g., hospital-insurance dyad). To do so may require going beyond the quantitative approach to qualitative approach (e.g., case studies). Connected to this area is the need to examine the evolution of analytical capabilities vis-à-vis maturity of business process capabilities.

CONTRIBUTIONS

This present research provides various contributions to research and practice. The current research addresses call to more theory-driven research on antecedents and consequences of firm's business analytics capabilities (Agarwal and Dhar 2014; Chen et al. 2012; Shanks and Sharma 2010). From a theoretical perspective, the research identifies a plausible mechanism through which firms build analytical capabilities. Since BA is in a preliminary stage of gaining awareness and adoption, the findings can potentially shed light on theoretical underpinnings explaining the differential ability to leverage analytics in organizations. Furthermore, the key contribution is that it facilitates a better understanding of the mechanisms through which firms can build analytical capabilities. The key message of the paper is the need to change the focus from mere existence of analytics as information processing mechanisms to development of analytical capabilities. The evolution of such capabilities is path dependent on firm's information processing approach–i.e., high alignment of information processing needs and information processing capabilities are essential to developing analytical capabilities. Only following best practices of adopting the best of business analytics functionality may not yield benefits. We also potentially contribute to the organizational value of IT literature (Barua and Mukhopadhyay 2000; Bhatta and Grover 2005; Lucas 1993; Meliville et al. 2004) by uncovering the antecedents

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of analytical capabilities that have not received much attention in prior research. By doing so, we show how firms can leverage business analytics and can potentially turn it into organizational value.

We contribute to research on healthcare IT implementations and its impact on organizational capability (e.g., Gardener et al. 2015; Seddon et al. 2013). We contextualize the existing IPT theoretical framework to healthcare domain by identifying healthcare IP mechanisms that can potentially affect the firm's analytical capability. Prior IS literature points to the uniqueness of the healthcare domain and challenges associated with HIT implementation and therefore represents a major context worthy of attention from IS scholars (Agarwal et al. 2010; Fichman et al. 2011). Such uniqueness accentuates the need for context-sensitive theorizing (John 2006; Whetten 2003). The study builds on and connects two different streams of literature (i.e., healthcare IS and IPT) to enhance our understanding of the how hospital's information processing capabilities in conjunction with information processing mechanisms facilitate the development of analytical capabilities. Thus by contextualizing it to the healthcare domain, we, therefore, contribute to the growing literature on healthcare IT implementations.

By investigating the theoretical underpinnings connecting hospital's IP approach and analytical capabilities, we address the call for more research on healthcare IT implementations and its impact organizational capability (Agarwal et al. 2010; Fichman et al. 2011). Given the substantial investment and focus on EHR implementations, managers and policy makers seek enhanced understanding of how these critical technologies can be leveraged towards efficient and cost effective healthcare systems (Hanauer et al. 2011; Lin et al. 2011). By identifying IP mechanisms by which EHRs can be leveraged to influence performance enhancing operational capabilities, we contribute to the theoretical understanding of the healthcare IT and value link.

Furthermore, the research contributes primarily to the nascent but growing literature on business analytics (e.g., Chen et al. 2012; Seddon et al. 2013; Shank and Sharma 2011). While the existing literature mostly focuses on the business value derived from the adoption of analytics, the present study emphasizes the need to move beyond mere resource perspective to the capability perspective.

For practice perspective, the research can offer a useful framework for managers to assess the organizational information processing strategy under which analytical capabilities can be built to better appropriate business value. The study emphasizes the need to align organizations information processing needs with information processing capabilities before pursuing analytics strategy. Furthermore, the study also underlines the need to ensure that integration of organizational business processes before expecting value from analytics strategy. Also, managers should recognize that complementarity of internal and external business process in facilitating analytical capabilities.

CONCLUSION

This study focuses on developing a better understanding of the relationship between hospital approach to information processing and its ability to build analytical capability. Drawing upon information processing theory, we develop a theoretical model that examines the connection between firms existing information processing mechanisms and its influence on analytical capabilities. We argued that the three organizational information processing mechanisms–i.e., extent of EHR use, CIS, and CIE–have a positive influence on firm's ability to build analytical capabilities. Furthermore, we argued that CIS and CIE will moderate the link between the extent of EHR use and analytical capabilities. In conclusion, we found full support for the main effects and lack of support for the interaction effects.

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APPENDIX A

Table 8: EHR Modules
Clinical data repository (CDR)
Clinical decision support systems (CDSS)
Computerized practitioner order entry (CPOE)
Order entry and order communication (OEOC)
Patient portal
Physician documentation
Physician portal
Pharmacy management system

Table 9: Information Exchange Initiatives
Agency for Health Research and Quality HIT Project
CMS HIE Projects
CMS's Chronic Care Improvement Programs
CMS's QIO Doctor's Office Quality Improvement Technology Program
Exchange of clinical information for transitions in care
Health Information Exchange/RHIO initiative
Nationwide Health Information Network (NwHIN)
Non-clinical Exchange Services
NwHIN Connect
NwHIN Direct
Other
Other (please specify)
Population/Public Health Reporting
State Level HIE/State Designated Entity
The exchange of information with disease & immunization registries
The participation in ACOs
The reporting of clinical quality measures to CMS
Clinical data repository

CHAPTER 3

ESSAY 2: ROLE OF ANALYTICAL CAPABILITY ON QUALITY OF CARE: AN EVENT SEQUENCE STUDY

ABSTRACT

Digital transformation of healthcare is increasingly dependent on IT-enabled business processes and analytical capability to deliver improvement in patient care outcomes. Although these innovations are in preliminary stages of incorporations into healthcare ecosystems, they hold vital importance to academic, practitioners and policy makers. While these innovations elicit interests, there exists a paucity of theory-driven research that investigates the mechanisms that connect IT enabled processes and analytical capabilities to patient care outcomes - vis-à-vis quality of care. In our effort to understand the mechanisms, we examine one such organizational factor–i.e. sequential integration of EHRs–as the differentiating factor that can explain above and beyond other indicators. Drawing upon the competitive progression theory, we develop a conceptual model that links organizational approach to the sequential integration of EHRs and analytical capabilities with hospital's delivery of quality of care. Using an event sequence method, we investigate if the sequence–i.e., reflecting unique path of adoption- in which hospitals integrate EHRs have significant impact on analytical capability. Furthermore, we also study the mechanism through which these sequences influence Quality of Care. Using multiple sources of data ($N = 155$), we examine the order in which EHRs are integrated and whether particular pattern of sequences yields enhanced value. Our results indicate that sequential integration of EHRs does matter and that hospitals that integrate EHRs based on operational model tend to have the higher analytical capability.

INTRODUCTION

Healthcare IT (HIT) is having a catalyzing effect on the healthcare industry. Since 2009, U.S government has been allocating $19 billion a year to encourage adoption of IT-enabled systems and processes to automate the healthcare workflow to improve the quality of care (IOM 2012; Terhune et al. 2009). Recent studies provide strong evidence to support the argument that HIT is associated with increase in healthcare performance–e.g., financial performance (Angst et al. 2010; Spaulding et al. 2013), operational efficiency (Bardhan and Thouin 2013; Das et al. 2011; Hillestad et al. 2005), patient satisfaction (Gardner et al. 2015), length of stay (Aron et al. 2011), reducing clinical uncertainty (Lanham et al. 2013), reducing mortality (Ash et al. 2010). The overall focus is on improving the quality of care. However, the research today has been unable to address the question of whether and under what conditions healthcare IT (HIT) will spur improvements in healthcare performance.

One of the early meta-analysis studies on the impact of IT on healthcare concluded that IT was effective in improving both cost and efficiency (Chaudhary et al. 2006). A follow-up meta-analysis by Goldzweiget et al. (2009) also validated the view that IT does impact healthcare performance metrics. In a more recent review of the literature indicate a wide variety of outcomes, ranging from positive to negative (Buntin et al. 2011). However, these studies fail to take into account the contextual factors and process changes that organizational experts believe are critical to successful implementation of IT system. These meta-analyses and a careful review of the literature indicates a wide variety of outcomes following HIT implementation, with little understanding of factors that influence healthcare performance metrics. Previous research presents some evidence of a positive relationship between the use of IT and quality of care outcome (e.g., Aron et al. 2011; Gardner et al. 2014; Queenan et al. 2011; Yu et al. 2009).

However, these works are limited in their ability to explain how healthcare IT interrelates with other organizational factors for better quality of healthcare.

The rush to digitize the healthcare workflow is generating a staggering amount of data into the organizational repository (Kawamoto et al. 2013; Tang et al. 2006). As a consequence, hospitals are relying on analytical capabilities to derive actionable insights, to improve decision-making, and to enhance the quality of care (e.g., Caban and Gotz 2015; Chen et al. 2012; Simpao et al. 2015). For instance, the advent of analytics has increased the scope for precision medicine initiatives (Simpao et al. 2015). It is possible to move now from evidence-based practices to more practice-based evidence from information generated through clinical care. Similarly, by leveraging data from multiple sources, it is now possible to develop analytically derived procedures that can utilize the medical, social, molecular, and environmental data of the patients to customize clinical care (Caban and Gotz 2015; Tenenbaum et al. 2016). Analytical capabilities make it possible to expose distinct molecular mechanism that constitutes the variations in disease manifestations (Collins and Varmus 2015). Furthermore, hospitals can utilize analyses of multi-dimensional data and mimic disease behavior across space and time (Tenenbaum et al. 2016).

Despite the apparent benefits of analytics, healthcare providers often report only modest improvements in the ability to make better clinical decisions using analytics (Caban and Gotz 2015; Ferranti et al. 2015). Literature from domains outside healthcare points to the fact that positive impact of analytics is not assured (Davenport 2006; HBR Analytics 2013). As a result of which, extant discourses has moved from mere BA implementation issues to emphasis on how to best harness the opportunities of BA capabilities (e.g., Bose 2009; Davenport 2006; Davenport and Harris 2010; Kohavi et al. 2002; Liberatore and Luo 2010; Popovic et al. 2012; Trkman et al. 2010). Specifically, in the healthcare context, there is a paucity of theory-driven research that

investigates the role of BA capabilities on the quality of care. Given the importance of analytical

capabilities to healthcare domain, theoretical understanding of the mechanism that connects

analytical capabilities to patient care outcome remains underdeveloped.

In our effort to understand these mechanisms, we specifically focus on the organizational

approach to the integration of IT-enabled healthcare business processes (i.e., EHRs). We

examine one such aspect–i.e., sequential integration of EHRs- as the differentiating factors that

can explain above and beyond other indicators. The sequential nature of HIT integration has

been known to explain variation in financial outcomes (e.g., Angst et al. 2011; Spaulding et al.

2013). The sequential nature of integration may reflect distinct organizational strategies pursued

by the hospital. These distinct strategies may be influenced by variation of existing technology,

hospital characteristics, geographic locations, etc. (e.g., Furukawa et al. 2008; Milstein et al.

2014; Spaulding et al. 2013). Also factored in are the unique contexts of integration of core

technologies. For example, uniqueness of operational workflow may necessitate adoption and

integration of specific technologies (e.g., Raghu and Vinze 2007; Spaulding et al. 2013)

Thus, the contingent nature of organizational challenges can motivate firms to follow unique

paths of EHR integration. These unique paths of integration also reflect the idea that

organizations learning is path dependent (Kogut and Zander 1992; Nonaka 1986)–i.e., each

subsequent integration of technology depends on the knowledge accumulated during over prior

integration (Rozensweig and Roth 2004).

Recent commentaries on the digital transformation of healthcare have identified the

measurement and quantification of healthcare IT payoff and its implication on patient outcomes

as a significant area of IS research (Agarwal et al. 2010; Fichman et al. 2011). However, the

theoretical and methodological significance of sequences in measurement and quantification are

yet fully explored. At the same time, there is the call to more theory-driven research on the role of business analytics capability on organizational performance (Agarwal and Dhar 2014; Chen et al. 2012; Shank and Sharma 2011). Although BA capabilities are built over firm's IT-enabled business processes (e.g., Davenport 2007; Isik et al. 2013; Trkman et al. 2010), little understanding exists on the impact of the sequence of integration of digitized core process on analytical capabilities. The present research fills this gap in the literature by developing a theoretical model that examines whether the sequence of EHR integration is associated with increased analytical capability. We ask the question: Do the sequence in which firms integrate the EHRs matter regarding building new capabilities or drive performance improvements? Furthermore, we explore the mechanism through which analytical capability influences the link between HIT and quality of care. Consistent with the idea that measurement is crucial to investigate the connection between hospital's EHR adoption and its ultimate impact on quality of care, we argue that sequence of EHR integration can potentially explain variance in analytical capabilities above and beyond other indicators.

Drawing on the competitive progression theory (Roth 1996; Rozensweig and Roth 2004) as the guiding theoretical framework, we develop a conceptual model that links the sequence of integration of EHR with analytical capability and performance outcomes in the context of healthcare. Furthermore, we use event sequence analysis to empirically test the proposed model using a merged dataset of U.S hospitals. More specifically, we examine how the sequence of EHRs–i.e., reflecting distinct paths of EHR adoption –impacts organization's analytical capabilities. We extend the sequence of integration to a unique model (i.e., operational model) of integration identified in the healthcare context. Simultaneously, we also examine the linkage between analytical capability and healthcare quality of care.

THEORETICAL FOUNDATION

This essay proposes that health care organizations ability to derive value from analytical capabilities are influenced by the sequence in which hospitals integrate EHRs–i.e., reflecting the integration of IT enabled digitized healthcare business processes- into the healthcare workflow. Various studies have pointed to the connection between EHR and performance outcomes (e.g., Ozdemir et al. 2011). However, organizations rarely integrate such critical components in a linear manner. The introduction of any new IT innovation is a complicated process that requires taking into account the interdependent nature of tasks and activities spanning functional and organizational boundaries. Given the complexity of the healthcare workflow, integrating any technology is a complex decision (Vest et al. 2010). To this extent, organizations take a more deliberate approach towards integrating key technologies, specifically EHR. The next subsection discusses the theoretical framework used for understanding the impact of sequences on analytical capabilities.

COMPETITIVE PROGRESSION THEORY

The interconnected nature of clinical and diagnostic processes makes integration of healthcare IT a complex and costly undertaking. Given the enormity of complexity, the literature suggests healthcare institutions tend to integrate EHR in a sequential manner (e.g., Milstein et al. 2014; Spaulding et al. 2013). The learning acquired over the process of integration is used towards integrating other EHR modules. Over time, a more preferred sequence will emerge that streamlines the learning process. Literature refers to this phenomenon as "learning to learn" processes (Levitt and March 1998). Such processes also have an impact on the organizational performance. Performance is improved when a simple process is integrated first followed by increased complex processes. As a consequence, patterns of integration are likely to yield

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heterogeneity in performance above and beyond the effect of individualized EHR operationalization. This essay examines whether the sequential nature of EHR integration ultimately impacts analytical capabilities. Based on the theoretical perspective, the learning acquired in the processes of sequential integration may potentially impact the building of other capabilities.

Two theoretical frameworks exemplify the sequential nature of firm's approach to developing competitive capabilities–i.e., the sand cone model (Ferdows and DeMeyer; Noble 1995) and competitive progression theory (Roth 1996; Rozensweig and Roth 2004). The theories suggest that the process of capability building can be conceptualized as a pyramid in which the base capability constitutes the foundation for the development of the next capability. Before building new capabilities, firms need to ensure that the operational competencies related with the capabilities are already developed are fully through organizational routines and sufficiently ingrained in the organization to achieve enhanced performance. That is, firms must consolidate the base capabilities (i.e., reflecting the base of the pyramid) before adding more capabilities on the top (Ferdows and De Meyer 1990; Nakane 1986; Rosenzweig and Roth 2004).

As firms develop the capabilities sequentially, a minimum level of the preexisting capability needs to be achieved before developing new capabilities. Thus, the capabilities that already established constitute the basis for the acquisition of subsequent capabilities. In other words, a minimum level of base capabilities serves as a necessary foundation for the establishment of new capabilities. The CPT theories suggest that as firms develop and improve its processes, it creates a base knowledge and skill set that enables it to use the accumulated knowledge towards building subsequent capabilities. Furthermore, the theories argue that ability to evaluate and utilize knowledge is largely a function of the level of prior related process

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knowledge. Each state of progression calls for increasingly higher levels of process knowledge integration and coordination.

The idea of sequential nature of capability building is consistent with Grant (1996) notion of sequencing as a method of knowledge integration. Grant (1996) argued that the simplest way in which firms can integrate specialized knowledge involves organizing routines in a time-patterned sequence. In the context of EHRs, hospitals will sequentially integrate these key IT enabled digitized healthcare processes to constitute the base capabilities needed to develop subsequent capabilities–i.e., analytical capabilities. The operational know-how derived as a result of integration forms the base knowledge for building following capabilities. As EHR modules are integrated, the accumulated base knowledge and skill set is used towards integrating following EHR modules.

A sequential series of EHRs reflect the unique path taken by the hospital in integrating digitized healthcare processes into the clinical and diagnostic workflow. This involves specialist knowledge associated clinical processes as well as knowledge of how these EHRs fit into users' activities. Acquisition of the operational know (i.e., learning effect) becomes critical to any sequence of capabilities integration. This interdependence also extends to the integration of analytical capabilities. Since BA capabilities are built over organizations digitized processes (Oliveira et al. 2012; Trkman et al. 2010), accumulated operational and functional know-how associated with the sequential integration of EHRs will form the base capabilities that will go towards building analytical capabilities. The value results not solely from the integration of single EHR, but that value intensifies as hospitals continue to sequentially integrate EHRs.

We contend that the sequence with which the series of EHR integration is transformed into competitive capabilities is a key indicator of the performance variations, but also distance

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proximity between sequences will be associated with greater variation in performance. The sequence of EHR reflects the mastering of the process complexity associated with the EHR integration. Over time, firms acquire the ability to value, assimilate and apply the new knowledge towards integration of other organizational capabilities (Cohen and Levinthal 1990; Leonard-Barton 1992). It is consistent with the idea that organizational learning is path dependent. In other words, past actions of the organization can predict the future course of actions (Clark 1996; Corbett and Van Waseenhove 1993; Hayes 1992; Hayes and Pissano 1996; Hayes et al. 2004; Kogut and Zander 1992).

QUALITY OF CARE

Prior literature indicates a variety of quality of care outcomes, ranging from positive to negative (Buntin et al. 2011; Gardner et al. 2014; Queenan et al. 2011; Yu et al. 2009). However, existing research provides limited insight in explaining how HIT interrelates with other factors for better quality of care outcomes. One such factor that can potentially explain how HIT interrelates with operational factors to account for the quality of care is the sequential nature of technology integration. For instance, some hospitals may integrate the CPOE and then subsequently integrate the clinical decision support system, while others may integrate the CPOE as the last EHR in the sequence of integration. As argued earlier, the complex and interdependent nature of the healthcare environment necessitates the building of IT capabilities in a sequential manner. Specifically, we ask whether and how this sequential nature of capability–i.e., sequence of EHRs -building explain variations in quality of care. While existing studies have shown the sequential nature of IT integration can have an impact on financial outcomes (Angst et al. 2011; Spaulding et al. 2013), does such sequences influence, directly or indirectly, patient related outcomes–i.e. quality of care?

Given the state of research, more understanding is required regarding how hospital's approach to EHR integration interrelates with other IT innovation (i.e., BA) to drive quality of care. More specifically, how does the sequential nature of EHR integration influence capability building vis-à-vis analytical capabilities? Although firms are eagerly building analytical capabilities, the benefits from such capabilities are not assured (Davenport 2006; HBR Analytical Services). Given the critical importance of analytics to the healthcare domain, limited understanding of the relationship between analytical capabilities and quality of care hinders our understanding the implications of firms' BA strategies and its subsequent benefits. While the literature suggests that sequences have an impact on hospitals financial outcomes, does this extend directly or indirectly to patient related outcomes reflect the quality of care? In the present study, care quality is an objective measure that assesses the hospital care processes on four common and severe health conditions: heart attack, heart failure, pneumonia, and outpatient care, and surgical care (Chandrasekaran et al. 2012; Gardner et al. 2013).

SEQUENTIAL INTEGRATION

As described earlier, sequential nature of technology integration reflects distinct strategies pursued by the hospital based on operational requirements (Spaulding et al. 2013). Prior literature suggests that IT-enabled business processes are firm's competitive capabilities (e.g., Gattiker and Goodhue 2007; Rai et al. 2012). These capabilities are developed and accumulated over time in a sequential fashion (Ferdows and De Meyer 1998). As firms integrate these capabilities, they acquire functional and operational know how that facilitates the integration of subsequent capabilities–i.e., reflecting path dependent nature of organizational learning (Kogut and Zander 1992; Roth 1996; Leonard-Barton 1992; Grant 1996).

Prior literature suggests that competitive capabilities, specifically IT enabled digitized processes, is path dependent in nature (e.g., Raghu and Vinze 2007). Integration of such competitive capabilities evolves over time. The learning acquired in the integration of a single capability is used towards integration of subsequent capabilities (Roth 1996). The rate and scale at which such learning happens are contingent on firm's approach towards integration. Specifically, literature identifies one such approach–i.e., operational model (e.g., Gattiker and Goodhue 2005; Premkumar et al. 2005; Raghu and Vinze 2007; Spaulding et al. 2013). Spaulding et al. (2013) investigated the impact of such sequence on cost factors and found that operational sequence of integration has more positive impact on cost compared to other types of sequence.

Integration models influenced by operational factors is mostly associated with the operational needs of the hospital's clinical and diagnostic processes–i.e., the fit between clinical and diagnostic process needs and IT needs. Hospital's routinized operational needs form the guiding principle on how it integrates core technology associated with clinical and diagnostic requirements (e.g., Ancker et al. 2014). For example, a healthcare organization's specific routine related to physician notes aggregation, prescribing, processing of drug ordering and administering the order may guide the processes of implementation of EHRs (e.g., Ford et al. 2009). Given such a routine, the hospital may first integrate the physician documentation system and then the computerized provider entry system. Thus, the operational routines dictate the manner in which EHRs are integrated into the healthcare workflow.

Extant healthcare IT literature also validates the idea of sequential integration of digitized healthcare processes, specifically EHRs (Milstein et al. 2014; Spaulding et al. 2013). The EHRs include systems like clinical documentation (e.g., inscribing physician and nursing notes),

clinical decision support systems, computerized provider order entry (CPOE), patient portal (i.e., personal health information), and health information management (IOM 2012). These EHRs modules are standalone systems that can be functionally integrated to accomplish the clinical and diagnostic task. Each module must work with other modules to create a functional system, and the interdependencies between them require complex decisions regarding which function to adopt, and in what order. For example, drug alerts using clinical decision support can only be implemented if patient medications are tracked electronically using computerized provider order entry or patient portal. Hospitals may prefer track patient medications (via CPOE) at the beginning of any clinical or diagnostic task (e.g., Lanham et al. 2012). Thus, it is evident each EHR integration is based on knowledge of the context. Hospitals may first integrate CPOE, acquire the operational and functional know-how by using it for an extended period and then integrate subsequent EHR modules. Since the modules are interdependent, knowledge gained incorporating a single module facilitates the integration of subsequent EHR modules.

We contend that as the integration of components into the overall organizational system evolves over time, its analysis should involve a temporal component instead of a "snapshot in time" approach. A possible method to investigate the temporal aspects of sequential implementation is through analyzing the sequence of integration of EHRs (e.g., Abbot 1983; Angst et al. 2011; Pentland 2003; Sabherwal and Robey 1993; Spaulding et al. 2013). For example, Angst et al. (2011) conducted a cluster analysis and found that the variation in sequence (patterns of integration) of integrated HIT have an impact on the cost outcomes. Similarly, Spaulding et al. (2013) found that variation in the pattern of integration has an impact on financial results. The present study investigates whether a sequence of EHRs affects firm's ability to leverage BA towards enhancing the quality of care. Consistent with the idea that

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measurement is crucial to investigating the connection between hospital's sequential approach to EHR integration and its ultimate impact on quality of care, we examine if that sequence of EHR integration can potentially explain variance in analytical capabilities above and beyond other indicators.

RESEARCH MODEL AND HYPOTHESIS

The research model draws on the competitive progression theory (Roth 1996; Rozensweig and Roth 2004). The conceptual model is described in figure (1). In the present study, we argue that a particular pattern of integration–i.e., *operational model* - of EHR will directly impact firm's analytical capabilities, which subsequently will influence the quality of care. A sequence of EHRs reflects temporally ordered events of EHR modules operationalized in the healthcare organization (e.g., Angst et al. 2011; Spaulding et al. 2013). Each element of the sequence is reflective of an event that happened in a particular point of time. Here, the event is associated with the integration of a specified EHR module.

In any sequence of event, time suggests the pacing of causality. *Temporal distance of EHR sequence* measures the proximity between the first EHR integration and the last EHR integration (e.g. Abbot 1990; Pentland 2003). The distance reflects the time taken to create the unique sequence in the organization. In other words, it indicates the gap between the occurrence of two events–i.e., integration of the first EHR module in the sequence and the last EHR module in the sequence. In the present context, the temporal distance reflects the accumulated base knowledge and skills set acquired as a result of the sequential integration of EHR capabilities. *Analytical capability* refers to the healthcare organization's ability to use business analytic tools to gain new insights related to healthcare performance, process effectiveness, and clinical care. The *quality of care* refers to the objective measure that assesses the hospital care process on four

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common and serious health conditions: heart attack, heart failure, pneumonia, outpatient care,

and surgical care (Chandrasekaran et al. 2012; Gardner et al. 2013). Construct definitions and

literature support for each construct in this study are summarized in Table 1.

Table 1: Definitions	
Variable	**Conceptual Definition**
Temporal Distance of EHR Sequence	*Temporal distance of EHR sequence* measures the proximity between the first EHR integration and the last EHR integration (adapted from Abbot 1990).
Quality of Care	Objective measure that assesses the hospital care processes on four common and serous health conditions: heart attack, heart failure, pneumonia, outpatient care, and surgical care (Chandrasekaran et al. 2012; Gardner et al. 2013)
EHR Sequence (Operational)	Reflects the temporal sequence of EHR integration influenced by operational factors (e.g., business process, routines)(Spaulding et al. 2013).
Analytical Capability	Healthcare organization's ability to use business analytic tools (e.g., querying, online analytical processing, dashboards, reporting, data mining) to gain new insights related to healthcare performance, process effectiveness, and clinical care.

Figure 1: Research Model
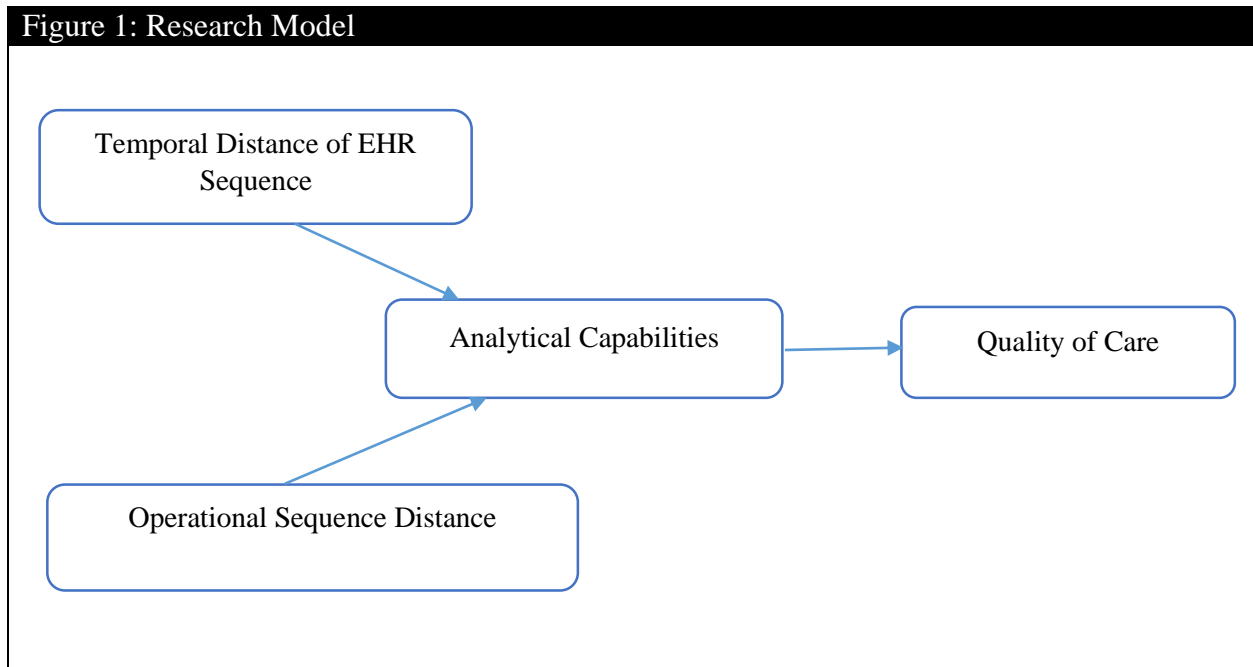
EHR integration reflects the temporal ordering of healthcare business processes (Milstein et al. 2014; Spaulding et al. 2013). Integration of EHR modules is a complex, costly and time-consuming undertaking. There are multiple challenges and constraints associated with such integration. As with any IT-enabled business process integration, it involves connection and synchronization with existing and new organizational processes (e.g., Barnes et al. 2002; Malone and Crowston 1994) and linking of activities or steps that may include connecting processes that span organizational boundaries (e.g., Kobayashi et al. 2003). Furthermore, the integration has multiple aspects–i.e., data integration, application integration, system integration, and organizational process integration (e.g., Barki and Pinsonneault 2005; Grant and Tu 2005).

Drawing on the CPT, we argue that each module of EHR integration calls for increasingly higher levels of process integration and coordination, beginning with the individual units and then expanding across functional and organizational boundaries. It involves addressing the process specificity–i.e., the tighter coupling of clinical and diagnostic activities- across interdepartmental units and inter-organizational networks. Various departments share of technical information and process knowledge cross functionality to ensure process specificity (e.g., Flynn and Flynn 2004; Kogut and Zander 1992; Voss and Winch 1996). With the integration of each EHR, hospitals expand their operational know-how by mastering the process complexity involved in integrating a single module. Since EHR capabilities are incorporated sequentially, the time between subsequent integration reflects the process time used towards the acquisition of learning acquired in the process of integration.

Therefore, the time between the sequential integration of the processes is associated with learning, which results in improved quality of processes (Goldratt and Cox 1984). Unimpeded flow of information can aid process learning (Argote 1999; Kerkhoff et al. 1998; Kogut and

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Zander; Leonard-Barton 1992) and reduce process variations (Berente et al. 2009). By increasing the depth of information sharing and the degree of process integration across units, hospitals can improve the quality of information input and output–i.e., accuracy, timeliness, accessibility, granularity, and transparency (Berente et al. 2009; Kock et al. 1997). Since business analytics systems are built over existing EHRs (e.g., Oleviera et al. 2012; Trkman et al. 2010) and consume the information feed from these digitized processes, the time associated with the maturity of integration process has a direct implication on the ability to gain actionable knowledge and insights. Therefore, we argue:

H1: *High temporal distance of between integration of EHRs will be associated with higher analytical capabilities*

Based on operational approach, the hospital may first integrate the CPOE and then the physician documentation system. An operational view of integration focuses on improving the process (e.g., reducing process variation) based on operational needs (Raghu and Vinze 2007). From operation view of process integration, the organization would seek points of excessive variation to start automation. As the firm sequentially integrates the EHRs, it acquires operational know how to reduce process variations in the subsequent integration. According to the CPT, when organizations integrate sequentially, organizations not only learn how to do the task better but also learn as to what tasks are even worth doing. Thus, as firms progressively integrate the EHR, they have more control over the process quality. Specifically, in the healthcare context, the operational model reflects fit between IT needs and business process requirements, (e.g., Spaulding et al. 2013). High process variations are associated with imperfect information and low process variance is related to information efficiency and high-quality information (Gimeno 1999; McCormick et al. 2009). Therefore, it may be safe to argue that EHR

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integration due to operational influence will result in low process variation leading to positive impact on analytical capabilities. Therefore,

H2: Sequence of EHR patterns closer to operational model of adoption will have greater impact on analytical capabilities.

Improving the quality of care processes involves identifying measures, defining targets, planning, communication, monitoring, reporting and feedback (e.g., Ratwani and Fong 2015; Simpao et al. 2015). Thus an approach relying on conventional wisdom to make decisions–i.e., use of benchmark or best practices-cannot be used to manage healthcare system. Correct relevant clinical and diagnostic decisions based on a large volume of internal and external data is only possible with BA capabilities that enable the analysis of data. Clinical data derived from EHRs contains longitudinal data of patient captured over time, with detailed records of patients' conditions, medication, treatments, and responses related to an individual's evolving health status. The large volume of clinical data, coupled with the complexity of the data set, makes it challenging to derive clinical and diagnostic patient care insights.

By pursuing sequential integration of EHRs, organizations have more control over the clinical process quality. When hospitals integrate the sequence based on the operational model, it reflects the alignment between hospitals process requirements and IT needs. By doing so, hospitals can acquire operational and functional know-how necessary to implement future integration. Hospitals gain operational expertise required to reduce process variations in the subsequent integration. High temporal distance reflects the maturity of operational and functional know-how associated with EHRs. The acquired knowledge base goes towards reducing process variations. High process variations suggest imperfect information and low process variation indicates high information efficiency and high-quality information.

By building analytical capabilities, hospitals can transform amalgamation of data into information that can improve patient outcomes, increase safety, and enhance operational efficiency. For example, analytical capabilities have increasingly become a critical component in the personalization of medication (Simpao et al. 2014; West et al. 2014). Using clinical analytics, caregivers can spot drug-drug interactions, which can potentially hinder patient's recovery process. Furthermore, analytical systems are also being used to enhance patient safety related to medication errors (Caban and Gotz 2015). Health organizations are using clinical analytics capabilities in developing clustering algorithms to predict disease progression paths and compare it with patients with similar disease. The insights derived can be used towards improving treatment best practices for diseases (Gotz et al. 2011). Therefore, by placing actionable insights into the hands of all the stakeholders, the analytical capability can have a significant impact on the quality of care. Thus, we argue that;

H3a: *Analytical capabilities will mediate the impact of temporal distance on quality of care.*

H3b: *Analytical capabilities will mediate the impact of operational sequence distance and quality of care.*

RESEARCH METHODS

To test the hypothesized relationships, we use three sources of data: HIMSS Analytics 2013; AHA IT Survey 2013, and U.S. Center for Medicare and Medicaid Services data (CMS). Each of the data set provides information associated with more than 4500 U.S hospitals. The HIMSS dataset contains data related to the EHR modules adopted by the hospitals. The AHA IT survey database includes information associated with functionality use for more than 4500 hospitals. CMS database provides data related to objective and subjective measure related to healthcare performance (i.e., quality of care) for more than 4000 hospitals. We merge the three

data set to create a single dataset. The three dataset were combined using the Medicare number, a unique identifier, given to any hospital that benefits from U.S government Medicare payments disbursement.

We use the HIMSS dataset to generate sequences of EHR integration in the hospital environment. Specifically, for the purpose of this research, we are interested in EHR modules a hospital has identified as operational. To generate an event sequence for individual hospital, we create a temporal sequence string using the operational year identified in the HIMSS database (e.g., Angst et al. 2011; Spaulding et al. 2013). Furthermore, we define an operational string (i.e., ideal type)-i.e. *Operational EHR sequence* - based on the literature and compare the similarity of the individual sequences to the defined ideal type. The AHA IT Survey provides the data associated with *analytical capabilities*. In the AHA survey data, hospitals were self-assessed on the extent to which specific functionalities related to business analytics were used for processing healthcare data. Besides our core research variables, several control variables were included to account for potential confounding effects. For hospital-level characteristics, we calculate the number of employees, age of the hospital, net operating revenue, Medicare, Medicaid, IS budget, hospital type (i.e., academic/nonacademic), and the location of the hospital (see Table 2).

Table 2: Controls	
Variable	**Operationalization (Using HIMSS Analytics)**
Age	Reflects the age of the hospital
Net Operating Revenue	Net operating revenue includes revenues associated with the main operations of the hospitals
Revenue Medicare	Percent of Medicaid that makes up the patient revenue at the hospital
Revenue Medicaid	Percent of Medicaid that makes up the patient revenue at the hospital
IS budget	IS department operating expense as a percent of total operating expense at the hospital
Number of EHRs	The count of EHRs operationalized in the hospitals workflow
Workflow redesign	Extent to which hospital has made changes to healthcare workflow to make optimal use of EHRs
Meaningful Use	Extent to which hospital is using certified EHR technology to improve clinical functions
$CPOE_{TIME}$	reflects the amount of time CPOE was operationalized prior to the integration of the next EHR.
$CDSS_{TIME}$	reflects the amount of time CDSS was operationalized prior to the integration of the next EHR.
PP_{TIME}	reflects the amount of time PP was operationalized prior to the integration of the next EHR.
PD_{TIME}	reflects the amount of time PD was operationalized prior to the integration of the next EHR.
PMS_{TIME}	reflects the amount of time PMS was operationalized prior to the integration of the next EHR.
HIM_{TIME}	reflects the amount of time HIM was operationalized prior to the integration of the next EHR.
CDR_{TIME}	reflects the amount of time CDR was operationalized prior to the integration of the next EHR.
$OEOC_{TIME}$	reflects the amount of time OEOC was operationalized prior to the integration of the next EHR.

The CMS database provides data related to the quality of care index. CMS data for

quality of care has been used in numerous studies (e.g., Boyer et al. 2012; Gardner et al. 2013;

Werner and Bradlow 2006; Yu et al. 2009). *Quality of care* is operationalized using the CMS

survey data (see Table 3). Specifically, we use the objective measure that assesses the hospital

care processes on four common and serious health conditions: heart attack, heart failure,

outpatient care, and surgical care (Boyer et al. 2012; Chandrasekaran et al. 2012; Garnder et al.

2013). Care quality consists of explicit and concrete outcomes that are objectively measured

using the survey regarding whether or not patients who should receive specific evident-based

care receive it. These measures have been widely used across multiple healthcare studies to

measure performance outcomes of individual hospitals (e.g., Boyer et al. 2012; Wernerand and

Bradlow, 2006; Yu et al., 2009). Consistent with the existing operationalization of overall

measure of care quality (e.g., Gardner et al. 2015; Queenan et al. 2011), we derived from the

CMS data as an aggregate measure of each hospital. We calculated the *quality of care* by

summing the counts of the process of treatments across all the measures, divided by the

summation of all the eligible cases (Boyers et al. 2012).

Table 3 : Quality of Care (CMS Health Data)	
Variables	**Operationalization (CMS Survey)**
Quality of Care	Please check all the QoC process indicators: **<u>AMI/heart attack measures</u>** Heart Attack Patients Given Aspirin at Arrival Fibrinolytic Therapy Received within 30 minutes of arrival Heart Attack Patients Given a prescription for statin at Discharge Heart Attack Patients Given PCI Within 90 Minutes Of Arrival **<u>HF/heart failure measures</u>** Heart Failure Patients Given Discharge Instructions Heart Failure Patients Given an Evaluation of Left Ventricular Systolic (LVS) Function Heart Failure Patients Given ACE Inhibitor or ARB for Left Ventricular Systolic Dysfunction **<u>OP/outpatient care</u>** Outpatients with chest pain or possible heart attack who got drugs to break up blood clots within 30 min of arrival OP-4 Outpatients with chest pain or possible heart attack who got aspirin within 24 h of arrival Outpatients having surgery who got an antibiotic at the right time – within one hour before surgery Outpatients having surgery who got the right kind of antibiotic **<u>INF/surgery and infection measures</u>** Surgery patients who were given an antibiotic at the right time (within one hour before surgery) to help prevent infection Surgery patients who were given the right kind of antibiotic to help prevent infection Surgery patients whose preventive antibiotics were stopped at the right time (within 24 h after surgery) Heart surgery patients whose blood sugar (blood glucose) is kept under good control 18-24 hours after surgery Surgery patients whose doctors ordered treatments to prevent blood clots after certain types of surgeries Patients who got treatment at the right time (within 24 h before or after their surgery) to help prevent blood clots after certain types of surgery

EVENT SEQUENCE ANALYSIS

We use the HIMSS Analytics database to derive the exact EHR sequences that were adopted by hospitals across the US. The database provides details about the EHRs and the year in which the hospital adopted and operationalized these systems. In the case of scenarios where the implementation date is not available, we dropped the hospital from our sample. This is to ensure that we have an accurate description of the sequence of adoption of the EHR modules. These steps were taken to ensure that we were able to derive a temporal path of EHR adoption of hospitals over time (e.g., Angst et al. 2011).

Event sequence analysis as a method has been used in many scientific studies (e.g., Abbot 1989; Pentland 2003; Joseph et al. 2012; Sabherwal and Robey 1993; Angst et al. 2011; Spaulding et al. 2013). Event ordering allows us to investigate the influence of variables in the sequences and provides insight as to if/how a specific pattern of events represents the context and process. In the present context, the operationalization of the EHR within the hospital is considered to be a single event. We take into consideration all the events (i.e., EHR modules) and construct a sequence of EHRs integrated into the hospital workflow. Each EHR module is taken to be an event. A temporal sequence of all the EHR integrated into the hospital environment forms the sequence string of EHRs. This sequence of EHRs forms the basic building block of our analysis. The EHR modules and the associated functionality is described in Table 10 (Appendix A).

Controlling Time

We construct a temporal view of each hospital's EHR integration sequence by tracking the year of integration of each EHR module. The event sequence technique emphasizes the

importance of taking into account the temporal component, rather than just the snapshot approach. Although the particular focus is examining the similarity of observed sequences of EHR to the derived ideal sequence, however, we also control for the time associated with the sequences. In cases of string sequences that reflect temporal regularities, costs may have a minor effect on the analysis. If proximity is being measured for identical sequences consisting of same elements, then the transformation associated with the proximity measures are limited. But if distance has theoretical implications– i.e., how long a particular state exists–then time plays a critical role in understanding the sequence. Thus, when the events are similar and sequences of actions are similar, the differentiating factor becomes the costs associated with the transformations.

In the present context, we use the process time associated with each EHR operationalization as controls for the theoretical model. The process time associated with a particular EHR reflects the amount of time the EHR was operationalized before the integration of the subsequent EHR in the sequence. In the present context, the process time reflects the learning that occurs before integration of other EHR elements in the sequence. In the case of process analysis, the orders of states and its transition are connected to time. When we posit that a particular state is inserted in or deleted from a specific sequence, we imply that a specific time shift occurs between the sequences. Thus our choice of controls is based on the time scale and its importance to the analysis. In essence, each element and the cost (i.e., process time) reflects the uniqueness of the organizational context in which the EHR was integrated. An element with an identical number of years may potentially reflect substantial organizational differences. Thus by considering each element and its process time as controls, we place the elements into their unique organizational context.

We construct a temporal view of each hospital's EHR integration sequence by tracking the dates of integration of each EHR module. HIMSS Analytics and IOM (2012) specifically identify 8 EHR modules (see Table 4) that collectively form a complete EHR system. The individual modules form the elements of the string. For example, if a hospital integrated EHR modules in the following years; CDR in 2003, PMS in 2006, HIM in 2007, PP in 2009, CPOE in 2013, and then the chronological sequence string derived would be CDR-PMS-HIM-PP-CPOE. Each EHR operationalized is represented by the element name in the temporal sequence of strings. Same time, we capture the process time of each EHR–i.e., reflecting the amount of time each EHR was in existence prior to integration of the next EHR in the sequence. In this case, the value of the controls $CDR_{TIME} = 3$, $PMS_{TIME} = 1$, and $HIM_{TIME} = 2$. Once we generate the sequence of integration, we compare and contrast the similarities and differences among sequences (i.e., also known as the optimal matching technique) as well as their relationship to analytical capabilities.

The proximity between EHR module integration in a sequence of EHR is measured using the temporal distance (Abbot 1990). The *temporal distance of EHR sequence* reflects the process time difference between the first and the last event in the sequence of event (Abbot 1990). In this case, the time gap between the first EHR integration and the last EHR integration reflects the temporal distance of a sequence of string.

Table 4: Elements of Sequence String	
Elements	**Integrated System**
CDR	Clinical Data Repository
CDSS	Clinical Decision Support System
CPOE	Computerized Practitioner Order Entry
OEOC	Order Entry and Order Communication
PP	Patient Portal
PD	Physician Documentation
HIM	Health Information Management
PMS	Pharmacy Management System

Sequence Generation

The operational perspective of IT implementation focuses on task automation with the primary intention to address time and cost savings (Klein 1995; Peppard and Rowland 1995). We use the clinical process boundaries to define the theorized sequence of EHR. These process boundaries are guided by the tasks associated with the three stakeholders–i.e., nurses, physicians, and pharmacists (Doolin et al. 2004). To generate the *operational EHR sequence* (i.e., operational model), we use the three stage medication management process based on the core operations–i.e., prescribing, dispensing, and administration (Kaushal and Bates 2002; Furukawa et al. 2008). The sequence is defined based on the series of clinical business processes identified from the literature.

Medication Management Context

In order to apply the operational models to the present context, we elaborate on the characteristics of a medication management clinical processes (Spaulding et al. 2013). We choose to use the medication management context for several reasons. First, existing clinical guidelines suggest a finite number of IT systems that are used in the three stages of medication management, thus providing boundaries for the analysis. Second, the order in which hospitals

adopt EHRs varies greatly, thus allowing us the opportunity to observe sequence heterogeneity. The process of ordering, verifying, dispensing, and administering prescription order are very well defined and are relatively consistent across US hospitals (IOM 2012).

The guideline for such process has been developed in order to ensure patient safety and adherence to regulatory rules (IOM 2012). Thus, the homogeneity in the clinical process allows us to observe whether the operational model of EHR adoptions can explain variability in a hospital's analytical capabilities. Third, the existing literature on IT payoff advocates examining performance at the level at which technology operates rather than extrapolating to higher organizational levels (e.g., Kohli and Deveraj 2003). Finally, we choose to focus on medication management context because of the ubiquity of this clinical processes across the US hospitals and form one of the key clinical workflows where policy makers emphasize greater process automation (Furukawa et al. 2008).

As suggested earlier, the operational model of adoption is defined based on the healthcare process sequence (IOM 2012). In order to create the sequence of EHRs, we use the context of medication management process within a hospital to derive the ideal operational sequence (Kaushal and Bates 2002; Furukawa et al. 2008; Spaulding et al. 2013). EHRs form the automated core clinical business process and are key systems associated with the process of administering medications and monitoring patients (Burton 2001; Bates 2003). Specifically, the present research focuses on the three core processes of medication management–i.e., *prescribing*, *dispensation*, and *administering*. The initiation of the process happens when a physician places a medication order for the patient (IOM 2012). The nurses associated with the process implement the physician's prescription order. Nurses add notes to the medical chart describing as assessments, interventions (including medications), and the response of the patient. When the

pharmacies receive physicians' orders they check the orders against the patient's charts and records to avoid any adverse effects such as drug interactions or allergic reactions. If the prescription meets the pharmacist's standards, the order is then processed. The medication is measured and mixed or counted in the pharmacy. It is then packaged and sent to the floor nurses for administration or dispensed to the patient.

Three Stages of Medication Management

To create an ideal EHR sequence (i.e., operational), we focus on the digitized core operations of the medication management workflow (Spaulding et al. 2013). Specifically, we include the eight EHR modules that support the three stage process–i.e., prescribing, dispensing, and administering. These eight systems represent the digitized IT-enabled clinical processes of core operations of the medication management process (Furukawa 2008; IOM 2012).

Based on the processes described earlier, the potential start point for this operational sequence is the CDR (Mackenzie et al. 2011). The process begins with accessing clinical data collected in the CDR through the course of clinical care for the patients. The system is used in conjunction with CDSS to assist in drug selection, dosing, and details related to the dosage durations (Koppel et al. 2009). CDSS aids in the clinical decision-making process at the point of care – i.e., drugs, laboratory testing, radiology procedures, and accessing clinical literature. The system integrates patient-specific and pathogen-specific information thus provides recommendations to the physicians (Kaushal and Bates 2002). The CDSS is used prior to physician's prescription entry through the CPOE. The CPOE standardizes the prescription orders, ensures legibility and completeness across the healthcare workflow. Furthermore, the CPOE provides timely information and about appropriateness and costs of medications, laboratories and radiological tests (Koppel et al. 2009; Van Der Sijs et al. 2006).

A physician's medication orders can either be generated by nurses using the OEOC module or can also be entered directly by the physician using the CPOE. The CPOE module specifically requires direct involvement of the physicians to enter the prescription. The CPOE requires direct input from the physicians to initiate a chain of other processes–i.e., order entry, patient engagement, documentations, amongst others. After the prescription is entered in the CPOE by the physician, the orders are received, and nursing orders are initiated through the OEOC module. Specifically, OEOC is used as part of clinical sub processes–i.e., care plan development and communication by physicians, order planning, entry, review and modification by nurses (Campbell et al. 2006; Wetterneck et al. 2011). Completion of these clinical subprocess initiates the interfacing between nursing and patients through the PP module.

The PP module provides patient engagement with care plans–i.e., draw the patient's clinical data directly from the ambulatory systems and, in turn, link the patient back to his or her primary care physician (Grant et al. 2010). The PD module is tightly associated with the PP module as it stores the details of the doctor and patient encounter based on clinical and regulatory codes (Schiff et al. 2010). The next step in the process is the initiation of the pharmacy process through the PMS–i.e., specific perceptions and automatic transmission of the electronic prescription to pharmacies (Jha et al. 2008). The identified pharmacies process the order using the PMS, and the medication is then sent to the nurses or released to the patients. Once the orders are processed through the PMS, HIM is used to track the medication (Schiff et al. 2010). This module is used at a global level and accessed by clinical staffs (e.g., nurses, physicians, pharmacists) (Wetterneck et al. 2011). Based on the sequence of clinical processes described above, we define the ideal operational sequence of EHRs (see Table 5).

Table 5 : Identified Operational Sequence (based on Operational Process)
CDR–CDSS–CPOE–OEOC–PP–PD–PMS–HIM

Optimal Matching Technique

Two approaches have been recommended for analyzing sequence data set (Abbot 1990; Abbot and Hrycak 1990). These approaches are based on the type of sequence data–recurring and non-recurring events. In case non-recurring event, optimal matching and multidimensional scaling technique have been recommended as the technique for exploring sequence data, specifically, if the data is non-recurring and is derived from a set of well-defined elements then the optimal matching technique has been used. Specifically, multidimensional scaling (MDS) deals with finding archetypes of sequences using other complementary techniques such as clustering, scaling, or grouping. For example, finding the sequences or subsequences that have maximum occurrence with the sequence data set. Whereas, the optimal matching techniques specifically focus on finding the resemblance between sequences.

The optimal matching technique has been predominantly used to measure the resemblance of sequences (e.g., Abbot 1990; Abbot and Hrycak 1990; Joseph et al. 2012; Sabherwal and Robey 1993). To apply the optimal matching algorithm, the sequences must be represented as a sequence string of well-defined elements drawn from an identified set. In this study, we define the elements (i.e., EHRs) drawn from a set of eight elements (see Table 3). A sequence in the present context is defined using a string of actions (i.e., EHR operationalization) from this set. Each EHR element reflects the temporal representation of year the module was operationalized in the hospital. For example, consider the sequential representation (SEQ1): CDR-PP-CDSS. The string suggests a sequence of three EHR implementation; CDR being the

first module implemented followed by PP and then CDSS. Similarly, another sequence may be

composed of the following sequence of events (SEQ2): CDR-CDSS. To measure the

resemblance between the two sequence strings, we evaluate the event sequence "distance"

(Abbot 1990). This sequence distance represents the number of actions (i.e., substitutions) that

would be needed to transform SEQ1 to SEQ2. The objective of the computation is to evaluate

the closest inter-sequence distance between the two sequences (i.e., SEQ1 and SEQ2) to measure

the resemblance between the two strings. The computation involves calculating all possible

transformations and then assign the minimum cost as the distance between the two sequence

strings.

SEQ A	CDR-CDSS-CPOE-HIM
SEQ B	PP-CDR-CDSS
SEQ C	PMS-HIM-CPOE-PP
SEQD	CDSS-CPOE-PP-HIM-PD-OEOC-PMS

     For sequence construction and comparison, we use the sequence programming method

using TraMineR (Gabadino et al. 2011). The method calculates the distances between sequences

–i.e., observed and references sequences. The distance reflects the similarity of the path of

integration of EHR modules to the reference sequences (i.e., operational). The distance calculates

the number of operations to transform one EHR sequence to another EHR sequence. In the

present context, the maximum number of operations to transform one EHR sequence to other is a

total of eight–i.e., since 8 elements in the set. Then distance is calculated for each hospital

against the reference patterns (i.e., operational model). In this study, sequence analysis reflects

the standard measure for how close each hospital's adoption path is to the operation model of

adoption. For example, sequence A can be transformed into sequence B by the insertion of PP

and deletion of CPOE and HIM. Similarly sequence A can be transformed into sequence D by deleting CDR at the beginning and inserting PD, OEOC and PMS at the end. In essence, we can loosely term sequence A as a closer sequence to B compared to D. This is because it takes only 3 actions to transform sequence A to sequence B compared to 4 actions for sequence D. Thus, the proximity measure can be seen as the measure of number of transformations required to transform one sequence to other. Smaller number of actions would suggest greater closeness compared to larger number of actions. Another important complexity associated with these transformation is the costs associated with each action. The costs are based on the theoretical assumptions associated with the model. In this case, the assumption is that the cost remains same for each transformation–i.e., 0 in case of a match and 1 in case of a mismatch. The output of the optimal matching technique is a matrix of inter-sequence distances that contain the minimum distances for all sequences from all other sequences. The summary statistics is shown in Table 6.

Table 6. Descriptive Statistics and Correlations

Variables (N = 155)	1	2	3	4	5	6	7	8	9
1. Age	1								
2. Net Operating Revenue	.149*	1							
3. Medicare	.020	-.036	1						
4. Medicaid	.013	.160*	.109	1					
5. IS Budget	.126	.391**	-.004	.131	1				
6. Number of EHRs	.060	.047	-.008	-.010	-.090	1			
7. Workflow Redesign	.102	.052	.028	-.009	.170*	.171*	1		
8. Meaningful Use	-.128	.047	.040	.290**	-.020	-.011	-.070	1	
9. CDR$_{TIME}$	-.087	-.011	.082	.383	-.033	.057	.068	.022	1
10. CDSS$_{TIME}$	.125	-.017	-.077	.019	-.057	-.028	.201	-.078	-.039
11. CPOE$_{TIME}$	.053	.033	.075	.020	-.001	.059	-.097	-.014	.341**
12. OEOC$_{TIME}$	.022	-.039	.029	.002	-.129	.051	.222**	.079	.267**
13. PP$_{TIME}$	.041	.131	-.006	-.044	.074	.108	.014	.035	-.367**
14. PD$_{TIME}$	-.051	-.068	-.067	.061	-.039	-.066	.085	.102	-.24**
15. HIM$_{TIME}$	-.047	.066	.039	-.011	.043	-.136*	.028	.112	.036
16. PMS$_{TIME}$	.024	-.011	.044	.006	-.098	.077	-.042	.059	.284**
17. Temporal Distance	.081	-.034	.055	-.015	-.111	.338**	.017	.028	-.059
18. Operational Sequence Distance	.011	-.007	-.010	-.023	-.017	.029	-.150*	.100	.135*
Mean	49.42	289.1	39.58	13.13	.03	4.81	2.94	76.23	.86
SD	39.9	40.09	10.93	3.99	.04	1.81	1.35	17.94	1.17

Variables (N=155)	10	11	12	13	14	15	16	17	18
10. CDSS$_{TIME}$	1								
11. CPOE$_{TIME}$	-.121	1							
12. OEOC$_{TIME}$	-.460**	-.075	1						
13. PP$_{TIME}$	.175*	-.064	-.016	1					
14. PD$_{TIME}$	-.272**	-.326**	.148*	.000	1				
15. HIM$_{TIME}$	-.189**	-.176*	-.176*	-.082	-.087	1			
16. PMS$_{TIME}$	-.049	-.126	-.126	.233**	.151*	-.318**	1		
17. Temporal Distance	-.002	.239	.162**	.053	-.113	-.066	.252	1	
18. Operational Sequence Distance	-.007	-.073	.063	.028	-.059	.050	-.041	.121	1
Mean	1.95	2.02	1.51	1.91	1.27	.99	.97	9.48	5.21
SD	1.98	1.73	1.43	1.96	1.68	1.85	1.15	3.04	1.63

Notes: *p < .05; **p < .01; ***p < .001

RESULTS

We tested for potential violations of least square assumptions–i.e., normality, linearity,

independent, and homoscedasticity. To test for possible violation of normality, we used the

Shapiro-Wilk test. The results are not significant (*p-value* > .05) thus suggesting the

observations are normally distributed. To test for any violation of independence, we used the

Durbin-Watson test. The results were well within the acceptable range of 1.50-2.50 (Greene

2008), thus suggesting a lack of any violation of independence. To test for violation of

homoscedasticity, we performed the Breusch-Pagan (1979) Lagrange multiplier test for

heteroskedasticity against the fitted values. The results lead to the rejection of homoscedasticity

($p < .05$). This leads to the conclusion that there is the presence of heteroskedasticity in our

model.

Given the presence of heteroskedasticity, we tested the hypothesized relationships using

weighted least squares (WLS) model. WLS addresses the inefficiency caused by the dependence

of the error term related to independent variables on analytical capabilities. Given the secondary

nature of the data, the dependence of the error terms can lead to overestimation of

underestimation of significant findings. WLS as a least square estimation technique mitigates the

risk associated with inefficient standard errors, which can potentially affect the significant testing

(Garen 1984). WLS provides an unbiased estimator by attaching a weight to each observation.

Based on recommendations by Hedges and Olkin (1998) and Hunter and Schmidt (2004), we

weighted each observations using a weight variable–i.e., the inverse square of the predicted

values.

The empirical model to be tested using WLS is as follows:

Analytical capabilities = $\beta 0 + \beta_1$ Ln(*Age*) + β_2 Ln (*Net Operating* Revenue) + β_3 Ln(*Medicare*) +

β_4Ln(*Medicaid*) + β_5 Ln (*IS Budget*) + β_6 (*No of EHRs*) + β_7 (*Workflow Redesign*) + β_8

(*Meaningful Use*) + β_9 (*CDR$_{TIME}$*) + β_{10} (*CDSS$_{TIME}$*) + β_{11} (*CPOE$_{TIME}$*) + β_{12} (*OEOC$_{TIME}$*) + β_{13}

(*PP$_{TIME}$*) + β_{14} (*PD$_{TIME}$*) + $\beta15$(*HIM$_{TIME}$*) + β_{16} (*PMS$_{TIME}$*) + β_{17} (Te*mporal Distance of EHR*

Sequence) + β_{18} (*Operational Sequence Distance*) + e

WLS Results and Mediation Tests

Table 7 shows the WLS regression results of the tested model. In the first hypothesis, we proposed a relationship between *Temporal Distance* and *Analytical capabilities*. The coefficient is positive and is statistically not significant (β=.*110*) suggesting a lack of significant association with hospital's analytical capability. Thus, the results do not provide support for H1.

In the second hypothesis, we proposed a relationship between *Operational sequence distance* and *analytical capabilities*. We find a significant effect of the sequence distance on analytical capabilities, thus supporting H2 (β=-.127*). The negative coefficient suggests that the closer distance is associated with high analytical capabilities and vice versa. In other words, higher operational distance is associated with lower analytical capability and vice versa.

In the third hypothesis, we argued that *analytical capabilities* (mediating variable (MV)) will mediate the impact of *temporal distance* (the independent variable (IV) and *operational sequence distance* (IV) on hospitals *Quality of Care* (dependent variable (DV)). To test the mediated relationships H3 (a, b), we conducted two statistical tests: (a) Baron and Kenny's (1986) four step mediation test and (2) Sobel's (1982) standard error test. First, using the steps of Barron and Kenny (1986), we find that there is no significant effect (p-value > .05) of *temporal distance* on *Quality of Care* without involving analytical capabilities. Second, we find that there is no significant effect (p-value > .05) of temporal distance on analytical capabilities. Third, we find a lack of significant effect (p-value < .05) of analytical capabilities on the quality of care. Finally, we find that in the presence of mediating variable (analytical capabilities), the effect of (temporal distance) on the quality of care as not significant (p –value < .05). The results suggest that analytical capabilities do not mediate temporal distance and quality of care.

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To ascertain the robustness of the Barron and Kenny (1986) test, we conducted the Sobel's (1982) standard errors test. We find that there was a no significant mediation effect of analytical capabilities (p > .05). Thus, the mediation hypothesis (H3a) is not supported. In our next step, we tested the mediating role of analytical capabilities (MV) on operational sequence (IV) and Quality of Care (DV). Applying the first step, we find no significant effect of (operational sequence) (IV) on Quality of Care (DV) without involving the mediational variable (i.e., analytical capability). Next, we found no significant effect of (operational sequence) on analytical capabilities. Third, we find a significant effect (p-value < .05) of analytical capabilities on the quality of care. The results suggest that analytical capabilities do not mediate the relationship between (operational sequence) and quality of care. Summary of the hypothesized relationships is shown in Table 8.

Table 7. Predicting Analytical Capabilities Using WLS					
	Controls		Main Effects		
R²	.28		.30		
ΔR²			.02		
	β	**SE**	**β**	**SE**	**VIF**
Age	-.094	.047	-.083	.046	1.157
Operating Revenue	.219**	.032	.238**	.032	1.236
Revenue Medicare	.003	.134	-.007	.133	1.068
Revenue Medicaid	.090	.123	.091	.122	1.140
IS Budget	.279***	.033	.259**	.033	1.283
Number of EHRs	.102	.022	.060	.024	1.236
Workflow Redesign	-.050	.030	-.045	.031	1.234
Meaningful Use	-.184*	.002	-.169*	.002	1.159
CDR$_{TIME}$	-.239*	.060	-.231*	.060	3.403
CDSS$_{TIME}$	-.061	.029	-.071	.029	2.101
CPOE$_{TIME}$	.070	.031	.056	.031	1.950
OEOC$_{TIME}$	-.163	.045	-.171	.044	2.667
PP$_{TIME}$	.006	.028	.016	.028	1.937
PD$_{TIME}$	-.183*	.030	-.186*	.030	1.657
HIM$_{TIME}$	.075	.027	.073	.026	1.560
PMS$_{TIME}$	.197	.059	.190	.058	2.979
Temporal Distance			.110	.014	1.295
Operational Sequence Distance			-.127*	.024	1.062
Notes: *p < .05; **p < .01; ***p < .001					

Table 8. Summary of Hypothesis Testing (WLS and Mediation Test)		
Hypothesis	**Description**	**Support?**
H1	Temporal Distance -> Analytical Capabilities	No
H2	Operational Sequence - > Analytical Capabilities	Yes
H3a	Temporal Distance - > Analytical Capabilities - > Quality of Care	No
H3b	Operational Sequence Distance -> Analytical Capabilities -> Quality of Care	No

In addition to the main analysis, we also conducted several robustness checks to examine the sensitivity of the results.

MULTICOLLINEARITY

We tested the presence of any multi-collinearity in our research model. Specifically, we analyzed if two more theoretical variables are linear combination of one another. The presence of such linear relationships would suggests that the least square estimates cannot be uniquely computed. As the degree of multi-collinearity increases, least square estimates become unstable leading to potentially inflated standard errors. We use the variance inflation factor (VIF) to detect if such conditions of linearity between variables exists. A VIF value above 10 suggests the possibility of multi-collinearity among the predictors (Goldberger 1991). In the case of the current regression model, the VIFs range between 1.06 and 3.40, which is well below the cutoff value of 10. Any predictor with the VIF value above 10 would merit further investigation to address the threat of multi-collinearity. Thus, our test suggests lack of any threat of multi-collinearity among the predictors in the model.

COMMON METHOD BIAS

To test for any potential threat of common method bias, we conducted Harman's Single factor test (Podsakoff et al. 2003). We used the factor analysis to test if a single factor accounts

for a large proportion of variance among all constructs (Podsakoff and Organ 1986). Single factors with large variance suggest the threat of common method bias. We did not find any such single component that can explain for any excessive proportion of variance. Each of the theoretical constructs explained variance ranging from 6.8% to 13.1% indicating a lack of any excessive threat from common method biases. The factor accounting for the large proportion of variance was 13.1%, which is below the cutoff thumb rule of 18% (Podsakoff 2000).

PROPENSITY SCORE MATCHING

Since we are using secondary data for testing the theoretical relationships, non-experimental nature of the data means it is entirely possible that the key assumption of random assignment is not met. The result of which, the data may be affected by observed and unobserved characteristics of the hospitals. Furthermore, it is quite possible that the assessed results overestimate or underestimate the true causal effect. We address this selection bias by using the propensity matching technique (Rosenbaum 1999). We use a dichotomous variable (i.e., CIS) as the treatment to stratify the observed data into two groups. The outcome of interests is the quality of care, and the independent variable is analytical capabilities. To generate the propensity score, we stratified the observed data into two groups–i.e., one where CIS does not exist (CIS =0; N= 59) and one where CIS exists (CIS=1; N= 96). Subsequently, we use the kernel matching probit estimator (Heckman et al. 1998) as the estimation method to calculate the propensity score. The propensity score for analytical capabilities was .98 (p-value < .05). The results suggest that hospitals differ significantly from those with a model with no explanatory variables. We also tested for the Wilcoxon Sign-Rank tests to check the sensitivity of the causal effect to potential violations (Rosenbaum 2002; Rosenbaum and Rubin 1983). Results of the test suggests a threshold factor of 213% ($\gamma = 2.2$; *p-value* < *.01*). From the result, we can infer that potential for

overestimation or underestimation of the true causal effect exists if we believe that hospitals with CIS are 213% more likely than comparative hospitals without CIS to be endowed with unobserved characteristics.

UNCAPTURED NONLINEARITY

To examine uncaptured nonlinearity, we tested for possible nonlinear combinations of explanatory variables having any power in explaining the dependent variable–i.e., quality of care. Significant results would suggest that the model is mispecified. We conducted the Ramsey RESET test (F = .31; p-value > .5) and did not find any support for model misspecification.

DISCUSSION

Both healthcare providers and policymakers are increasingly devoting substantial resources to improving the delivery of quality of care. To do so, there is increasing attention on EHR integration and building analytical capabilities. Literature suggests EHR integration is a complicated process, typically combined incrementally in a deliberately planned sequence over time. Same time, the research suggests that building analytical capabilities is a challenge. While research has separately highlighted EHR integration and analytical capabilities, this is one of the first studies that links the sequence of EHR integration to the building of analytical capabilities in the US hospitals.

The results of the analysis provide partial empirical evidence of the research model. First, we did not find any statistically significant relationship between the temporal distance of sequence of EHR and analytical capabilities (h1). We argued that temporal distance between IT-enabled digitized core processes reflect the learning effect acquired as a result of exploration and exploitation of systems. As hospitals pursue integration of digitized core processes, the operational know-how requires mastering the process complexity. The process time used towards

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the acquisition of learning acquired in the process of integration. Thus, the time between the sequential combinations of the processes is associated with learning, which results in improved quality of processes. However, we did not find support for our argued relationship. A potential explanation for the lack of significance could be lack of theoretical variables for capturing the amount of exploration and exploitation pursued by the hospitals. We know from the literature that organizational learning is a function of these two dimensions (i.e., exploration and exploitation) (March 1991). Future studies can test the existing model by incorporating the concepts of exploration and exploitation into the theorized model.

Second, we found that sequences closer to operational model of integration have a significant effect on analytical capabilities (h2). The operational view of digitized process integration emphasizes on the reduction of process variations (Raghu and Vinze 2007). The operational view reflects the time-tested codified routines integrated into the organizational workflow. From the operational point of view, hospitals would seek points of extreme variation to start the automation processes. As EHRs are integrated, exploration and exploitation over time will lead to a reduction in process variations. Since analytical capabilities are a function of digitized core processes, low process variations will be associated with enhanced analytical capabilities.

Third, we found no support for our mediation hypothesis (h3a, h3b). We did not find empirical evidence to support our argument that analytical capabilities mediate the relationship between temporal distance, operational sequence and the quality of care. A plausible explanation for the lack of association could the nature of analytical capabilities. Analytical capabilities could be conceptualized as a lower-order capability that are tailored and configured to form advanced level capabilities, which in turn influence quality of care. In essence, there could potentially be

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other organizational capabilities that could mediate the relationship between analytical capabilities and quality of care.

LIMITATIONS AND FUTURE RESEARCH

We identify some of the limitations of our research, which also provides some fruitful opportunities for future studies. First, we assess the homogeneity of hospital's EHR adoption in a cross-sectional dataset. We assume that the cross-sectional data reflects each hospital at a unique point in their integration sequence. Thus our sample only contains data where we were able to create an EHR series path. To create a path, only those sequence that has three or more EHR integration were considered. While we were able to incorporate the time horizon over which the hospital's sequence was created, however, we cannot assess whether results would differ if we were to test it using longitudinal data. While our hospital level data enables us to control the effect of contextual factors–e.g., IS budget, Medicare, Medicate -, however, future research can test the theoretical model in other domains to confirm the generalizability of our current findings.

Another key limitation of our work is that our results do not address the causal mechanism that drives a hospital's decisions about the sequential integration of EHRs. Our interpretation of the results is associational. It is essential to examine the causal nature of the relationships. Although beyond the scope of present inquiry, it would be insightful to consider the adoption stages (early vs. late) of specific hospitals and the cost-benefit analysis that went into the integration of specific sequences. As we know that the healthcare as an industry is heavily regulated by the industry norms, what role do institutional pressures have on the adoption and integration of the EHRs? The present theoretical arguments and the methodological approach does not allow us to incorporate these other factors. Future research could explore

these causal mechanisms that influence the strategic decisions that lead to the sequence of integration and its subsequent implications on firm's ability to build and leverage analytics.

In the present study, we restrict our focus to particular type IT-enabled digitized capability (i.e., EHRs) and a specific organizational capability–i.e., analytical capability. There is ample scope to extend the theoretical model to incorporate other IT capabilities (e.g., inter-organizational management, IS/business partnership, vendor management). Same time, it would be useful to investigate antecedents and consequences of the various organizational approach to IT integration. Although our analysis is quantitatively driven, future studies can take a qualitative approach (e.g., case studies) to unravel the connections between the evolution of other organizational capabilities and its implication on analytical capability. Another potential rich area of research can be the examination of organizational leadership and its implication on the evolution of analytical capabilities.

CONTRIBUTIONS

Firstly, the present study answers the call for a more comprehensive theoretical framework that links analytical capabilities with performance outcomes (Chen et al. 2012; Shank and Sharma 2010). In doing so, we contribute to the theoretical understanding of the linkages between firms' approach to IT-enabled business process integration and value derived from analytical capabilities. As companies build analytical capabilities, the findings can shed light on the theoretical underpinnings explaining the differential ability to leverage analytics in organizations. The key message of the paper is the need to focus on IT-enabled process integration strategies as the base capabilities needed to build analytical capabilities. Mere adherence to analytics related best practices may not yield benefits. The evolution of analytical capabilities is path dependent on firms existing IT-enabled digitized processes. Furthermore, we

contribute to contextualized theory development (John 2006; Whetten 2009) in the healthcare domain. By doing so, we provide unique theoretical insight into how hospitals approach to EHR integration has consequences on its ability to deliver increased quality of care.

Secondly, one of the key contributions of the present research is the emphasis on event sequence analysis as a viable and relevant methodology for investigating organizational performance. Recent commentaries on the digital transformation of healthcare argued the need for extensive studies on measurement and quantification of HIT payoff and its implication on patient care outcomes (Agarwal et al. 2010; Fichman et al. 2011). Our study emphasizes the theoretical and methodological significance of sequences in measurement and quantification of process-based studies (Van de Ven and Poole 1990). We demonstrate the viability of sequence analysis to develop and test process theories of organizational change and development. Examining the order of integration allows us to view the evolution of a process as opposed to a single snapshot in time and lends insight into the process of integration instead of exclusively focusing on the outcome of integration. The method utilized in the study provides a rigorous time-sequenced examination that yields an overarching insight: the ability to appropriate organizational value from analytical innovations is dependent on firm's approach to core business process integration. The manner in which companies integrate core processes has a direct implication on businesses ability to derive performance outcome from BA use.

Thirdly, we contribute to the nascent, but growing IS literature on business analytics (e.g., Isik et al. 2013; Popovic et al. 2012; Shank and Sharma 2011). Furthermore, we also contribute to the IS literature on healthcare IT implementations and its impact on organizational performance (e.g., Gardner et al. 2015; Spaulding et al. 2013; Queenan et al. 2011). The study builds on and connects two different streams of literature–i.e., HIT and CPT–to enhance our

understanding of hospital's approach to IT-enabled process integration and development of analytical capabilities.

Finally, from the practitioner's perspective, hospital's ability to exploit the volume of organizational data depends on its ability to leverage BA. However, the presence of BA does not automatically translate into value for the hospital. Managers need to focus on the dependencies that enable hospital's BA capabilities. Specifically, managers need to concentrate on the IT enabled business processes and the strategies used towards integrating digitized business processes. In essence, managers should pay additional attention to ensure that integration of these core business processes is based on the operational needs of the hospital.

CONCLUSION

This essay examines how a sequence of EHRs–i.e., reflecting the unique and distinct path of EHR integration–impacts organization's business analytical capabilities. Specifically, we consider a particular approach to EHR integration–i.e., operational model- in the healthcare context. We investigate the proximity of hospitals integration sequence to the operational model and its impact on analytical capabilities. Furthermore, we also examine the mediational role of analytical capability on the relationships between HIT and quality of care. Drawing on the competitive progression theory, we develop a conceptual model that investigates the theoretical mechanism by which firm's approach to EHR integration impacts analytical capabilities and subsequently impacts the quality of care. Our results suggest that is a strong association between sequential integration based on operational model and hospital's analytical capabilities.

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Table 8: Analytical Capabilities	
Variables	**Operationalization (AHA IT Survey Data)**
Analytical Capabilities	**Please indicate whether you have used electronic clinical data from the EHR to:** **Performance analytics** - Create a dashboard with measures of organizational performance - Create a dashboard with measures of unit-level performance - Create individual provider performance profiles - Generate reports to inform strategic planning **Clinical analytics** - Identify care gaps for specific patient populations. - Identify high risk patients for follow-up care using algorithm or other tools **Process analytics** - Create an approach for clinicians to query the data - Assess adherence to clinical practice guidelines - Maximize quality improvements

Table 9: EHR Functionality	
Elements	**Integrated System**
CDR	Facilitates leveraging of the clinical data collected through the course of clinical care for the purpose of patient care. CDR facilitates standardization of clinical data by providing the clinical data warehousing system. Provides an electronic version of patient's care plan including their medication schedule (Mackenzie et al. 2011)
CDSS	Assists in drug selection, dosing, and duration. Incorporates patient-specific or pathogen-specific information and provide advice to the physician. Aid the clinical decision-making process at the point of care –i.e., drugs, laboratory testing, radiology procedures, and clinical reference literature. The clinician uses the module after viewing the recommendations (Kaushal and Bates 2012).
CPOE	Standardizes orders, ensures legibility and completeness. Provides timely information, provide feedback about appropriateness and costs of medications, laboratories and radiological tests, allow easy implementation of clinical pathways. Electronic entry for treatment of patients under the physician's care (Koppel et al. 2009; Van Der Sijs et al. 2006)
OEOC	Receive physician's orders and initiates nursing orders. Used by clinical staff (e.g., nurses, ward secretaries, etc.). Performs the sub processes of (1) care-plan development and communication by physicians; (2) order planning by nurses; (3) order entry by nurses; (4) order review and modification by nurses (Campbell et al. 2006; Wetterneck et al. 2011)
PP	Interfacing system between nursing and patients; access to patient's personal health information. Acts as informatics-based interventions that include (1) patient engagement with care plans. Draw the patient's clinical data directly from the ambulatory EHR and, in turn, linking the patient back to primary care physician (Grant et al. 2010)
PD	Clinically driven workflow based on clinical and regulatory information; stores details of physician and patient encounter based on clinical and regulatory codes (Schiff et al. 2010)
HIM	To help ensure that medications are properly administered and tracked. Used at a global level and accessed by clinical staffs (e.g., nurses, physicians, pharmacists) (Wetterneck et al. 2011)
PMS	Used to process the pharmacy – i.e., specific prescription. Automatic transmission of electronic prescriptions to pharmacies (Jha et al. 2008)

CHAPTER 4

CONCLUSION

The following chapter outlines the summary of research finding of each essay.

Essay 1 investigated the role of organization's approach to information processing and its ability to enable analytical capabilities. We used the *Information processing theory* to argue that organizations ability to build analytical capabilities is path dependent on the approach to addressing uncertainty associated dearth of information. Specifically, we identified two such uncertainties–i.e., process uncertainties and relationship uncertainties. Based on the literature, we argue that these two types of organizational uncertainties have significant implications on enabling firm's analytical capabilities. Based on these uncertainties, we identified three information processing mechanism–i.e., *Extent of EHR use*, *clinical information standards*, and *collaborative information exchange*- capable of influencing firm's analytical capabilities. We tested our argued relationships using secondary databases (i.e., HIMSS Analytics 2013 and AHA IT Survey 2013) consisting of data related to more than 5000 hospitals. Specifically, we hypothesized that these distinct information processing mechanisms have a positive influence on firm's ability to enabling analytical capabilities. Based on the empirical evidence, we found full support for these relationships. In addition to the main effects, we also argued that *clinical information standards* and *collaborative information exchange* will moderate the relationship between the extent of EHR use and analytical capabilities. Based on the analysis, we did not find any empirical support for the moderating relationships.

Essay 2 investigated the role of organization's approach to the integration of IT-enabled core business process and its implication on firm's analytical capabilities. Specifically, we examine how sequences of EHRs–i.e., reflecting the unique path of integration–could explain the

difference in firm's analytical capabilities above and beyond other indicators. Furthermore, we consider a particular approach to EHR integration–i.e., operational model–in the healthcare context. We draw on the competitive progression theory (CPT) as the guiding theoretical lens to develop a conceptual model that examines if the sequential approach to the integration of EHRs impacts firm's analytical capabilities and health care performance–i.e., quality of care. We argue that the learning acquired in the process of sequential integration impacts the building of other organizational capabilities. Based on the CPT, we contend that the process of capability building can be conceptualized as a pyramid in which the base capability constitutes the foundation for the building subsequent capabilities. Building organizational capabilities necessitates that the operational competencies supporting the capabilities are already developed and are full codified into organizational routines. Using an event sequence analysis, we empirically test the research model using a merged dataset of U.S. hospitals. Our results suggest that is a strong association between sequential integration based on operational model and hospital's analytical capabilities.