Journal of Operations Management 41 (2016) 25–41

Contents lists available at ScienceDirect

Journal of Operations Management

journal homepage: www.elsevier.com/locate/jom

The impact of Health Information Technology bundles on Hospital performance: An econometric study

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ARTICLE INFO

Article history:
Received 4 June 2015
Received in revised form
13 October 2015
Accepted 19 October 2015
Available online 1 December 2015
Accepted by Mikko Ketokivi

Keywords:
HIT
Healthcare delivery
Cost
Quality of care
Econometric study

ABSTRACT

Hospitals are characterized by high levels of technical expertise as well as patient interactions. In an attempt to improve their performance along these dimensions, hospitals are making significant investments in health information technologies (HIT). However, the performance benefits from these investments are largely unknown. This study employs a portfolio approach to study HIT adoption using a large longitudinal panel data for 3615 US hospitals from 2007 to 2012. Insights from the Advanced Manufacturing Technology (AMT) and existing HIT literature are used to categorize 76 HITs into 3 distinct bundles based on their extent of patient centered integration, and the extent of caregiver interaction. We then examine how two key HIT bundles: Clinical HIT (defined as HIT systems primarily used for patient data collection, diagnosis and treatment) and Augmented Clinical HIT (defined as HIT systems primarily used for integrating patient information and augmenting decision making capability of caregivers) jointly impact cost and process quality outcomes. Cost is measured in terms of total hospital operating expenses per bed while process quality is assessed along two dimensions: conformance quality or the ability to adhere to technical standards and experiential quality or the ability to cater to preferences of the patient. Results suggest complementarities between Clinical and Augmented Clinical HIT with respect to process quality but not cost outcomes. A follow-up post-hoc analysis which divides Augmented Clinical HIT into Electronic Medical Record (EMR) and Non-EMR technologies offers additional explanation to the lack of association with cost. We discuss these implications to both theory and practice of HIT adoption.

1. Introduction

Advances in information technology (IT) have altered the interface between customers and service providers in numerous professional services settings such as banks, hotels and legal services (Froehle and Roth, 2004). A study by Lewis and Brown (2012) sheds light on the challenges associated with IT implementation, noting that while the firm studied had invested heavily in recent years in distinct IT systems, "the benefit of this type of automation was clear to some but questioned by others" (p. 7). There is a strong concern in professional service firms regarding the trade-off between the benefits of "distilling knowledge in a reproducible form" versus "treating human beings like bits on a conveyor belt" (Lewis and Brown, 2012: p.12). While Lewis and Brown examine a legal firm, this same sentiment is very common in professional service settings such as hospitals characterized by high levels of technical standards (that lend themselves to standardization) as well as many patient interactions (which are much more heterogeneous). Studies show that hospitals struggle to simultaneously improve on conformance quality focused on technical standards as well as experiential quality that is focused on interactions with the patients (Chandrasekaran et al., 2012). Recent changes in reimbursements by the Centers for Medicare and Medicaid (CMS) penalizes hospitals if they do not show improvement on both these process quality outcomes.

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http://dx.doi.org/10.1016/j.jom.2015.10.001
0272-6963/

Health Information Technology (HIT) offers one potential avenue to successfully improve on both conformance and experiential quality. To promote HIT adoptions, the US government passed the Health Information Technology for Economic and Clinical Health (HITECH) Act in 2009 offering stimulus payments of approximately $27 Billion over the next 10 years to eligible hospital systems (HITECH, 2009). Government policy initiatives such as the HITECH Act have had a huge impact on hospital operations, with the average capital expenditure per bed on HIT increasing by 62% from 2010 to 2011, while total capital expenditure in the same hospitals increased by only 2.6% (Cerrato, 2013). In dollar terms, HIT spending is estimated to be $34.5 billion in 2014 while maintaining a steady growth to reach $56.7 billion in 2017 (Manos, 2013; Cerrato, 2013).

Given this emphasis on HIT, numerous scholars have called for empirical evidence on the relationship between HIT and hospital performance (Agarwal et al., 2010). Following these calls, studies have examined the impact of HIT on hospital performance. These studies however yield mixed results and report either a positive impact (Devaraj and Kohli, 2003; Aron et al., 2011), marginal improvements (McCullough et al., 2010) or negative impact (Koppel et al., 2005) on hospital performance. Potential explanations for these conflicting results include limitations such as focusing on a single technology (Kohli and Devaraj, 2004; Wang et al., 2003; Koppel et al., 2005), a lack of consideration for the user/systems interface, and looking at hospital performance measures such as readmissions and mortality that are subjected to several patient characteristics (DesHarnais et al., 1990).

Our study overcomes the above limitations by taking a portfolio approach to study HIT adoption and builds on existing HIT and advanced manufacturing technologies (AMT) literature (Meredith, 1987; Boyer, 1999). Recent studies on HIT have recognized the need to study these technologies in bundles (e.g. Angst et al., 2012). We extend this idea by using insights from AMT literature and categorizing HIT based on patient-centered integration and caregiver interactions. We define patient centered integration as the degree to which various HITs allow exchanging, coordinating and effectively utilizing patient health records (excluding administrative data such as billing, insurance, payroll, etc.) to enhance the delivery of care. The second dimension, caregiver interaction, encompasses the degree to which a given HIT is intended to facilitate the work of caregivers such as physicians and nurses (excluding administrative support staff). Based on these dimensions, we categorize HIT into three distinct bundles: (1) Administrative HIT which constitutes technologies that have minimum levels of patient-centered integration and almost no caregiver interaction, (2) Clinical HIT which constitutes technologies that have moderate levels of patient-centered integration (primarily responsible for collection of patient data and helping with diagnosis and treatment) and are used infrequently by caregivers. Finally, (3) Augmented Clinical HIT which constitutes technologies that have a high degree of patient-centered integration and also requires extensive caregiver interaction. Given the minimal to no caregiver interactions with Administrative HIT, our study primarily investigates the relationships between Clinical HIT and Augmented Clinical HIT, after controlling for Administrative HIT, on cost and process quality outcomes. Specifically, the following research question is addressed in our study: *How do Clinical HIT and Augmented Clinical HIT jointly affect cost and process quality outcomes?*

We collect longitudinal data on 76 HIT and their adoption status from 3615 U.S. hospitals during the period 2007–2012 to examine our research question. Cost performance is measured in terms of hospitals' operating cost per bed, while process quality is measured in terms of conformance quality – the level of caregivers' adherence to evidence-based standards of care (Boyer et al., 2012), and experiential quality – the caregivers' ability to adapt interactions to patients' specific needs (Chandrasekaran et al., 2012). The rationale to investigate the effects of HIT adoption on the process quality outcomes (e.g., conformance and experiential quality) rather than the final quality of care outcomes (e.g., mortality and readmissions) is supported by the following facts. First, studies have shown that final quality of care outcomes such as mortality and readmissions are strongly associated with several diagnosis-related group (DRG) characteristics (DesHarnais et al., 1990) and process quality outcomes (Senot et al., 2015) and hence may not be ideal to study HIT adoption. Second, studying the effects of HIT on final clinical outcomes requires a well-established technology infrastructure which is certainly not the case for a vast majority of U.S. hospitals (Jha et al., 2009). Finally, studies have shown that IT adoption in professional service settings must balance the standardization of procedures with the ability to customize customer care (Lewis and Brown, 2012). A similar reduction in process quality can be detrimental for hospitals that are now being reimbursed by CMS based on their conformance quality and experiential quality scores. Hospitals are at risk losing as much as 2% of their Medicare reimbursements if they do not show improvements in both their conformance and experiential quality scores beginning fiscal year 2013.

Results from our analyses indicate complementarities between Clinical and Augmented Clinical HIT with respect to process quality outcomes but not with respect to cost outcomes. To understand the lack of complementarities with cost, we conducted a post-hoc analysis by looking within the Augmented Clinical HIT bundle. Specifically, we divided Augmented Clinical HIT into Electronic Medical Record (EMR) and Non-EMR technologies. EMR HITs form the basic set of technologies that are required for linking patient records (Furukawa et al., 2010). These technologies have been the primary focus of adoption following the HITECH Act regulations in 2009 (HITECH, 2009). The post-hoc analysis shows that EMR HIT – Clinical HIT interaction is positively associated with cost while the non-EMR – Clinical HIT interaction is negatively associated with cost thereby canceling each other in our main analyses. We also find both EMR and non-EMR HITs benefit process quality outcomes. Taken together these results offers important insights to hospital administrators on cost-quality tradeoffs when implementing HITs. In addition, we also highlight synergies between HIT bundles which can be instrumental in achieving simultaneous improvements in conformance and experiential quality outcomes.

2. Theoretical background

2.1. Technology adoption in healthcare professional service setting

Numerous studies in service settings have argued for a positive association between IT investments and firm performance (Brynjolfsson and Hitt, 1996; Boyer, 1999). However, findings from these studies may not be directly transferable to the hospital professional service settings due to several reasons. First at the organizational level, Harris (1977) described hospitals as a non-cooperative oligopoly with caregivers and administrators focusing on competing objectives – effective care vs. efficient operations. Second, at the individual caregiver level, there is considerable tension between physicians in different specialties as well as between physicians and nurses with respect to the healthcare quality outcomes (Pronovost and Vohr, 2010). For instance, physicians are more focused on the technical aspects of care delivery (i.e., conformance quality) while nurses are considered to be experts in engaging with patients and families and hence are considered to be chief architects to improve experiential quality. These differences between physicians and nurse can augment the trade-off between standardization and human (e.g., patient) interactions evidenced in hospitals (Chandrasekaran et al., 2012). It can also create preferential bias towards the adoption of certain HIT bundles while imposing additional challenges in the adoption of others. Given these dynamics, it is not surprising that studies examining the impact of HIT on hospital cost and process quality outcomes have yielded mixed results. Table A2 in Appendix A summarizes some of the key findings from this literature stream.

A couple of insights are worth noting from this literature. First, researchers have often studied HIT adoption at a smaller scale and focused on a limited number of technologies. For instance, Devaraj and Kohli (2000, 2003) employ data from eight hospitals from the same healthcare systems to document improvements in lagged mortality rates as a function of HIT investments. Similarly, Kucher et al. (2005) document improved clinical outcomes due to the adoption of a computer alert program for physicians using data from 2500 patients at a single hospital. In a study of two hospitals, Aron et al. (2011) found that investments in automating error prevention systems resulted in fewer medical errors. While these results consistently provide support for the value of HIT in improving outcomes, the use of small sample sizes limits the generalizability of results while focus on a limited number of technologies fails to incorporate the complementarities amongst different HIT bundles. Since hospitals adopt HIT not as a standalone systems but bundles of technology, the results from these studies do not provide conclusive support to the association between HIT and performance.

Second, a large number of studies in the extant literature have only looked at a single performance dimension when evaluating the impact of HIT. For example, Queenan et al. (2011) found a positive association between Computerized Physician Order Entry (CPOE) use and patient satisfaction which was found to be stronger for non-academic hospitals. Similarly, Menachemi et al. (2006) studied the impact of Clinical, Administrative and Strategic technology on a hospital's financial performance. They found a positive association between HIT use and financial metrics like revenues, cash flows, etc. This focus on a single performance measure fails to capture potential tradeoffs between multiple performance measures (Chandrasekaran et al., 2012) while adopting HITs. Third, even the studies that have looked at multiple performance dimensions have primarily focused on final quality of care measures such as mortality and readmissions which have several flaws as identified earlier. For example, Han et al. (2005) showed a positive association between CPOE use and mortality rate. Similarly, DesRoches et al. (2010) found no association between the use of EMR and a hospital's performance along mortality, length of stay and readmission. Measures such as mortality and readmissions are affected by several diagnosis-related group (DRG) characteristics (DesHarnais et al., 1990) and process quality outcomes (Senot et al., 2015; Angst et al., 2012). Thus HIT likely is one among a multitude of factors that impact such high level outcomes. A focus on process quality outcomes is therefore more useful while investigating the performance benefits from HIT investments.

Finally, a vast number of studies have used cross sectional data to evaluate the impact of HIT on performance. For example, Linder et al. (2007) using cross sectional data for his study found no association between the use of electronic health records and quality of ambulatory care. Similarly, Koppel et al. (2005) using cross sectional data found that the use of CPOE facilitated 22 types of medication error risks. Numerous operations management studies have documented the lengthy learning curve between the technology adoption and improvements in performance (Boyer, 1999). Thus using data from a given point of time may not be ideal to study the impact of HIT on performance.

In an overview of the extant research, Agarwal et al. (2010) identify two major gaps when studying HIT adoption and call for more research to address these gaps. First, they note significant heterogeneity in hospital employees (e.g., caregivers vs. support staff), both at the organizational level (i.e., hospital) and at the individual level thus making it important to account for the degree and type of interaction of technology with these heterogeneous groups. Second, Agarwal et al. (2010) argue that technology has often not been clearly conceptualized and bounded. In particular, many researchers have examined individual technologies rather than integrated systems. They note that there are about 100 different HIT applications and note as an example that "early investment in digitizing patient information may produce no obvious benefit to performance until the decision support component is added" (Agarwal et al., 2010: 802).

We build on and link these calls for research in two specific ways. First, we account for a significant aspect of heterogeneity in hospital employees by accounting for the extent of interaction of technology with caregivers and support staff. Second, we examine bundles of HIT technology and their relationship to performance outcomes over a period of several years. In what follows, we elaborate more on our approach to categorize HIT bundles.

2.2. Categorization of HIT systems

Our study uses insights from the advanced manufacturing technologies (AMT) research to categorize HITs into bundles (Meredith, 1987; Boyer, 1999). Broadly captured, AMT research finds that the benefits from technology acquisition is the result of two factors: 1) integration of multiple stand-alone technologies and 2) the recognition of the critical interactions with the users (Meredith, 1987; Boyer, 1999). We seek to apply these principles to examine HIT as an amalgamation of multiple technologies and recognize its degree of interface with the caregivers (e.g., physicians, nurses).

In a study of AMTs, Meredith (1987) wrote that the true benefits of technology only emerge when "separate islands of automation" begin to merge or integrate. This finding was replicated and enhanced in work by Boyer et al. (1997) and Boyer (1999). The current study seeks to apply this principle by accounting for the level of patient centered integration when categorizing HITs. Similarly, AMT research emphasizes the need to recognize the relationship between human users and the technological systems as a critical foundation for success (Snell and Dean, 1994; Boyer et al., 1997). This study accounts for this finding by incorporating the extent of caregiver interaction in our classification of HITs, i.e., we posit that it is the form in which caregivers (as opposed to hospital personnel not centrally interacting with patients) interact with HIT systems that is critical.

There are indeed as few studies that have adopted a portfolio approach to HIT adoption which are worth mentioning (Angst, Devaraj, & D'Arcy, 2012; Burke et al., 2002; Menachemi et al., 2006). For instance, Burke et al. (2002) categorize HIT into Strategic, Administrative and Clinical bundles based on their functions. Similarly, Angst et al. (2012) grouped HITs into Clinical and Administrative HITs. Although these studies are advancing our knowledge on the performance benefits from HIT by recognizing the complementarities between multiple technologies, they fail to acknowledge that hospitals have two separate data flows dealing with administrative and patient data and that different HITs are used to integrate and manage them. Moreover, these studies fail to account for the fact that HITs dealing with patient data will be more closely related with delivery of care whereas administrative HITs will have a greater impact on efficiency of operations. Finally, they also fail to recognize that HITs dealing with patient data (mostly categorized as clinical HIT by these scholars) may have different levels of interactions with caregivers thus impacting their work routines to different degrees. For instance, certain HIT systems such as Material Management deal with administrative data and their primary objective is improving efficiencies. On the other hand HITs like Computerized Practitioner Order Entry (CPOE) and Cath Labs deal with patient data. While CPOE heavily rely on physician inputs, Cath Labs is primarily used by lab technicians with some levels of interactions with the physicians and nurses. Failing to account for these different data flows and the levels of user interactions may result in an incomplete understanding of how these HITs impact hospital operations.

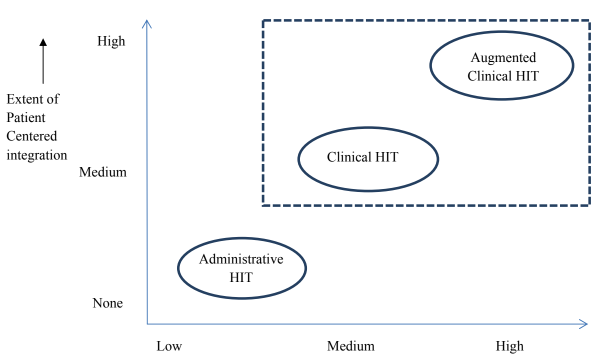
We address the limitations in existing HIT classification schemes by accounting for the extent of patient centered integration and levels of interaction with caregivers. Fig. 1 represents our approach to categorize HIT bundles. Based on these dimensions, we divide HITs into three distinct categories: Administrative, Clinical and Augmented Clinical. A q-sort process (described later in the study) is then used to classify 76 HITs into these 3 categories. Table A1 in Appendix A demonstrates the assignment of individual technologies to these categories.

Administrative HIT are primarily associated with administrative information flows within a hospital, including many accounting and financial systems that help in the efficient operation of the hospitals. These systems are not integrated with patient care systems and caregivers (e.g., physicians, nurses) rarely interact directly with these technologies. An example of Administrative HIT system is Enterprise Resource Planning which integrates hospital wide support functions. Similarly a Staff Scheduling system which creates automated scheduling for hospital personnel based on skill levels, shifts, seniority is an Administrative HIT system because it does not deal with patient data and has minimal interaction with Caregivers. Given the minimal to no caregiver interaction, our study controls for the investments in these systems but do not posit hypotheses regarding their effects on healthcare outcomes.

Clinical HIT are designed to improve patient care and primarily deal with collection, testing and processing of patient data for medical purposes or in treating patients. An example of Clinical HIT is Computerized Tomography which uses x-rays to generate virtual slices of internal body parts in order to diagnose tumors, fractures, etc. Similarly an order entry system which is a legacy system that allows patient data entry from desktop computers at different locations within the hospitals (e.g., nursing stations) but has limited reporting, integrative or decision support capabilities is classified as Clinical HIT.

Clinical HIT systems are relatively independent from each other (e.g., an order entry system and a CT scan machine) and are primarily used for data acquisition, rather than decision making. As such caregiver interaction, while substantial, is at a lower level due to the relatively unidimensional nature of the data captured. A vast majority of these systems have been present as islands of automation across U.S. hospitals since early 1980s.

Augmented Clinical HIT integrates several Clinical HIT systems and further adds decision support and reporting capabilities to the data collected by clinical systems. These systems are designed to be used as relatively holistic tools by the caregivers with the greatest decision making authority (i.e., physicians and nurses). An example is a Clinical Decision Support System that accesses patient medical and demographic data from different sources and combines it with relevant research to help in diagnosis. Similarly a nurse staffing/scheduling system which makes nurse staffing decisions based on patient volume, acuity levels, etc. is an Augmented Clinical HIT. This is because a nurse staffing/scheduling system integrates the use of administrative and patient data to make decisions, adds decision support (via automation) and reporting capabilities and is primarily designed for use by nurses. Augmented Clinical HIT is substantially more complex than Clinical HIT and is primarily focused on integrating various clinical technologies. These systems are relatively new to the HIT world with systems such as EMR showing an adoption rate of 7.6% in the year 2008 (Jha et al., 2009).



	Clinical HIT	Augmented Clinical HIT	Administrative HIT
Core Functions	Patient data collection, diagnosis and treatment	Patient data integration. Reporting and decision support for caregivers	Administrative data integration. Improve operational efficiency by integration and substitution of labor.
Typical Users	Technicians, Nurses and Physicians	Nurses and Physicians	Administrative Staff
Major Emphasis on Adoption	Pre HITECH Act. Continued emphasis since the 1990s	Continued emphasis post the HITECH Act which was passed in 2009	Pre HITECH Act. Continued emphasis since the 1980s

Fig. 1. Hospital information technology bundles.

3. Research hypotheses

3.1. HIT bundles and cost performance

In this study, we use hospital's operating cost per bed as a measure of their cost performance. According to CMS, operating cost includes expenses such as employee salaries, supplies, training investments and other technological investments (e.g., procuring new HITs, warranty, customization, etc.) and will reflect the efficiencies gained by the HIT assets.

We argue that investments in Clinical HIT can positively affect hospital efficiencies and hence can reduce operating cost. Studies show that investments in Clinical HIT allow hospitals to eliminate inefficiencies in their care delivery process (Staggers, 2004; Watcharasriroj and Tang, 2004). In fact, Clinical HIT systems such as Order Entry systems can improve information flow (Soh and Markus, 1995), and helps codify patient information (Borzekowski, 2009) which avoids additional rework and errors. Clinical HIT systems also help standardize procedures and policies across various entities within the hospital setting (Borzekowski, 2009). For example, Vital Sign Monitoring systems can be set up to continuously monitor patients' condition without the need for dedicated caregivers which can enable immediate detection of abnormalities thus enabling timely treatment and reduced costs (Smith et al., 2006). These systems are also designed to feed information collected from the patient directly into the hospital database thus preventing manual errors and eliminating rework associated with multiple data entries for the same patient. All these evidences suggest a positive relationship between investments in Clinical HIT and cost performance.

The relationship between Augmented Clinical HIT and cost performance may not be that direct. For instance, Augmented Clinical HIT encompasses tools such as CPOE that can allow integrating various functions within the organization leading to faster information flow, improved responsiveness and reduced rework (Li and Collier, 2000; Kumar and Motwani, 1999; Das and Teng, 1998). This may reduce operational inefficiencies due to poor communication and loss of information at the functional boundaries and hence may improve cost performance. However, Augmented Clinical HIT systems are considerably expensive investments for the hospitals (Poon et al., 2004). For instance, studies have shown that CPOE adoptions can cost between $3–10 million depending on the size of the hospital (Poon et al., 2004). In addition to these initial investments, actual adoption of Augmented Clinical HIT requires substantial cultural transformation that can be extremely expensive (Kuperman and Gibson, 2003). The recent emphasis on Augmented Clinical HIT following the HITECH Act indicates that a majority of hospitals are still in the cultural transformation and adjustment period. For instance, systems such as Clinical Decision Support and Physician Documentation are relatively new technologies adopted by the hospitals in recent years. In fact, studies show that physicians especially in major teaching hospitals are reluctant in using new Augmented Clinical HIT systems owing to the magnitude of change triggered in their work routines (Lapointe and Rivard, 2005). As a result, hospitals are forced to invest extensively in mandatory training programs that can result in significant operating expense. A vast majority of hospitals are in the early phases of investing in Augmented Clinical HIT systems (Jha et al., 2009) thus requiring the need for them to bear costs associated with this adjustment period. These arguments suggest that the cost involved in adopting Augmented Clinical HIT may outweigh its benefits during the initial stages of implementation.

Although Augmented Clinical HIT may increase hospital operating costs, high levels of Augmented Clinical HIT allows hospitals to have better information systems, reporting structures and interunit coordination mechanisms. Under these circumstances, using Clinical HIT leads to improved visibility and helps monitoring clinical issues amongst various entities within the hospital. In fact, research shows that integrating multiple technologies eases codification of knowledge, improves access to organization wide data and standardization of procedures (Galbraith, 1973). This suggests positive moderation relationship between Augmented Clinical HIT and Clinical HIT with respect to cost performance. These arguments are supported by the complementarity theory (Milgrom and Roberts, 1995) which states that the presence of similar resources can increase the benefits achieved from organizational resources. Augmented Clinical HIT not only integrates the data collected by Clinical HIT but also adds reporting and decision support capabilities. Thus Augmented Clinical HIT can complement Clinical HIT and may increase the value of information collected by Clinical HIT. For example, a hospital with high Augmented Clinical HIT will have integrated patient records and decision support capabilities. This will enable caregivers to combine patient test results with their medical history and use decision support capabilities to make more informed decisions. In this situation High Augmented Clinical HIT increases the value of the information collected and diagnosis performed by Clinical HIT systems. Further, substitution of labor by automation and reduced rework in Clinical data entry and analysis which is achieved at higher Augmented Clinical HIT levels will also strengthen the relationship between Clinical HIT and cost. This leads to our hypothesis regarding the relationship between Augmented Clinical and Clinical HIT.

Hypothesis 1. *Augmented Clinical HIT positively moderates the relationship between Clinical HIT and cost performance such that the benefits from Clinical HIT on cost performance increases with an increase in Augmented Clinical HIT*

3.2. HIT bundles and conformance quality

Conformance quality is defined as the degree of adherence to predefined standards (Garvin, 1987). In this study we define conformance quality as the degree of adherence to the Center of Medicare and Medicaid Services (CMS) process quality measures at a hospital for four conditions namely Heart Attack (AMI), Heart Failure (HF), Pneumonia (PN) and Surgical Care Improvement Project (SCIP). We argue that conformance quality improves as a result of complementarities between Clinical and Augmented Clinical HIT.

Clinical HIT systems are involved in collecting patient data, diagnosis and treatment. Hence hospitals that have high levels of Clinical HIT can collect patient data and identify their conditions quickly. This can not only enable faster diagnosis and more accurate treatment but can also result in improved and better compliance to customized standards based on the patients' condition (Bates and Gawande, 2003). For example, a highly automated hematology lab can use analyzers to quickly and accurately diagnose infections in admitted patients. This can result in caregivers having better compliance to procedures and treatments specific to patient conditions. Similarly, investments in Chart Deficiency tracking systems helps identify and monitor patient characteristics which further allows caregivers to better comply with the technical standards. All these arguments suggest a positive relationship between Clinical HIT and conformance quality.

Augmented Clinical HIT systems can also help hospitals meet technical compliance. Besides benefits of integration, reporting and decision support, Augmented Clinical HIT systems allow standardization of routines by codifying protocols directly into the systems. It also allows developing a customized checklist of protocols that need to be followed for individual patients based on their condition and medical history. Presence of such systems can help monitor patient progress and track compliance shortfalls to specific caregivers. Thus, Augmented Clinical HIT systems will not only increase compliance to predefined protocols but also increase accountability from these measures. For example, a CPOE system with decision support can be designed to set up alerts for platelet count, weight, baseline lab results and even provide recommendations on dosage amounts when prescribing antibiotics. This will help ensure compliance to standard protocols under surgical care improvement project (SCIP) based on the patients' specific condition. These arguments suggest a positive association between Augmented Clinical HIT and conformance quality.

Furthermore, investments in Augmented Clinical HIT can also improve the effectiveness of Clinical HIT through better integration, reporting and decision support functionality. This argument is supported by the information processing theory (Galbraith, 1973, 1974) which classifies Augmented Clinical HIT as coordination mechanism designed to reduce uncertainty due to cross department integration of patient data and standardization of procedures and data exchange protocols. For instance, research shows that uncertainty in the patient medical condition is one of the reasons that influence caregiver assessment for a patient, which will influence treatment protocols (Arrow, 1963; Wennberg, 1985; Balsa et al., 2003). A number of times medical tests need to be conducted and matched with the patient's medical records to resolve this uncertainty. In order to meet conformance quality on a number of CMS process quality measures time is of the essence. For example, one of the protocols states that heart attack patients need to be administered fibrinolytic medication within 30 min of arrival. However these medications have been shown to be harmful in case of internal bleeding (MedlinePlus, 2013). Therefore uncertainty in the patient condition needs to be resolved before delivering these medications. Better integration of data collected by Clinical HIT (medical test results and patient medical history) should lead to a faster resolution of the uncertainty around the patient condition and improve conformance quality. For example, Immunoassay Clinical HIT systems are capable of running ST2 tests which can help monitor biomarkers levels in heart patients on a regular basis. A fully integrated Electronic Medical Records system will be able to transmit the Immunoassay results quickly to caregivers while providing them guidelines on steps that need to be followed based on the patient condition. ST2 levels have been shown to be correlated with increased risk of mortality and readmissions in heart patients (Bayes-Genis et al., 2010). Hence regular and accurate monitoring of these levels will result in better compliance and clinical care. Thus, the presence of a strong Augmented Clinical HIT infrastructure at a hospital can strengthen the relationship between Clinical HIT and conformance quality. This leads us to the next hypothesis.

Hypothesis 2. *Augmented Clinical HIT positively moderates the relationship between Clinical HIT and conformance quality such that the benefits from Clinical HIT on conformance quality increases with increase in Augmented Clinical HIT*

3.3. HIT and experiential quality

Experiential quality represents the quality of interaction between patients and caregivers as perceived by the patient. Rich interactions with patients can allow hospitals to capture patient's individual concerns and integrate them into their clinical decisions. Studies have shown that high levels of experiential quality scores are associated with reduced readmissions and improvements in quality of life upon discharge (Boulding et al., 2011; Senot et al., 2015).

A number of studies have argued for reduction in customer experience in professional services settings as a result of new technology adoption due to the adaptation process that new technology and the organization have to go through before its benefits are fully realized (Rice and Rogers, 1980; Tyre & Orlikowski, 1994). This adaptation process is required because new technologies rarely fit the organizational needs perfectly. The adaptation process may require changes to the technology (e.g., addition of new functionality) and changes to the organization (e.g., development and adoption of new technology aided work routines).

Clinical HIT technologies are not new to hospitals and may not disrupt work routines among the caregivers. For instance, computerized tomography systems which use x-rays to generate virtual slices of internal body parts have been in use since the mid-1970s and are commonly used Clinical HIT system at hospitals (Filler, 2009). As a result, investment in these systems does not pose significant disruptions to the work routines for the caregivers. In addition, Clinical HIT also leads to more accurate and faster diagnosis of patients' conditions which can reduce the communication loop back with the patient thus leading to a better overall patient experience. For example, a hospital that has made investments in Clinical HIT in the form of an in-house clinical laboratory can achieve better turnaround times on patient specimen tests. This would improve experiential quality because nurses and physicians in these hospitals can have better and accurate communication regarding patient conditions and treatment options. All these evidence suggest a positive association between Clinical HIT and experiential quality.

Due to the recent emphasis on Augmented Clinical HIT following the HITECH Act, most hospitals caregivers are still in the process of adjusting to the new routines created by the introduction of the Augmented Clinical HIT systems. For instance, according to a study by Jha et al. (2009) the adoption rate for a basic EMR system in the United States in the year 2008 was at 7.6%. This adjustment period requires caregivers to spend increased amount of time to learn the new systems and adjust to the new routines all in the presence of the patients. This can result in reduced patient experience. A number of studies have also talked about potential increase in customer dissatisfaction as physicians start using computers and hand held devices to enter and retrieve information during the patient interaction (Ford et al., 2009; Jha et al., 2009). As the comfort of caregivers to these new systems increases the negative impact of Augmented Clinical HIT systems on experiential quality may diminish. However, given the newness of these systems in vast majority of hospitals, we argue that Augmented Clinical HIT will negatively affect patient experience.

We also argue that Augmented Clinical HIT negatively moderates the relationship between Clinical HIT and experiential quality due to the following reasons. Although, Augmented Clinical HIT has the potential to improve the effectiveness and capabilities of Clinical HIT, it is a relatively newer technology which can cause significant disruptions in the work routines of the caregivers. For example, Scott et al. (2005) found that a mismatch between organizational routines and EMR adoption in hospitals can result in increased resistance from physicians and a decision to abandon the installation process. This transition phase can also result in a reduction in the time spent with patients. For instance, although hospitals with high Clinical HIT achieve fast turnaround on patient data collection and diagnosis, integrating these test results using Augmented Clinical HIT may require that caregivers spend additional time and effort with the new technologies. This additional time commitment on the part of caregivers may reduce the quality of their interactions with patients and has been shown to increase patient dissatisfaction (Ford et al., 2009; Jha et al., 2009). Hence, Augmented Clinical HIT systems should reduce the impact of Clinical HIT on experiential quality. This leads to the next hypothesis.

Hypothesis 3. *Augmented Clinical HIT negatively moderates the relationship between Clinical HIT and experiential quality during the HIT adaptation stage such that the benefits from Clinical HIT on experiential quality decreases with increase in Augmented Clinical HIT*

4. Research methods

4.1. Data collection

We collected secondary data from 3615 U.S. acute care hospitals (unit of analysis) for the years 2007–2012 to test our hypotheses. Specifically, data from five secondary data sources were combined for the analysis. Sources include HIMSS for individual technologies that constitute HIT bundles, CMS process of care for conformance quality, CMS HCAHPS for experiential quality, Medicare Cost Reports for cost data and CMS Impact files for control variables like Case Mix index (CMI), Teaching Intensity, etc.

Although data for HIT were available from 1975, we decided to look at HIT adoption during the years 2007–2012 due to the following reasons. First, a period starting from 2007 provides a good window to capture the ramp up in HIT infrastructure by hospitals in anticipation of HITECH Act which was passed in 2009. Prior to this time frame, adoption for HIT bundles (especially Augmented Clinical HIT) was more sporadic without any significant trends. Furthermore, public reporting of a number of metrics including HCAHPS survey that is used to measure experiential quality started during the 2006–08 timeframe making 2007 as a logical starting point. The combined dataset includes 3615 US hospitals from 51 states. Hospitals with less than 25 beds were excluded from the study due to their low likelihood of needing a strong technology infrastructure because of their small size. Further rehabilitation centers, psychiatric centers and veteran administration centers were excluded from the study due to their significantly different operations and patients compared to acute care and specialty hospitals.

HIMMS Analytics was used to get data on HIT bundles in hospitals over time. HITs that were common across the 6 year panel i.e., appear in the HIMSS database for each year were included in the study. This ensured that the base number of technologies remains the same and that relatively new technologies that were added to the HIMSS database do not skew the results. All 76 technologies included were standalone technologies and had clearly defined functionalities according to HIMMS analytics. This minimized concerns regarding duplication of technologies in our sample. In addition, HITs that are marked as “Live and Operational” in the HIMSS database are used to determine HIT adoption. The use of “Live and Operational” technologies should effectively eliminate obsolete and unused technologies from consideration.

4.2. Dependent variables

4.2.1. Cost performance

This is a measure of the operating costs incurred by a hospital per bed. It is calculated by dividing the net operating expenses of a hospital by the number of beds as reported in the CMS cost reports. A natural log of the cost per bed is used for the study. A log transformation is applied to the measure to reduce the impact of outliers and satisfy conditions of normality for the regression model.

4.2.2. Conformance quality

This variable is evaluated based on CMS quality of care measures. A logit transformation (Collett, 2003) of the weighted average (P_i) of the percentage compliance along four dimensions namely Heart Attack (AMI), Heart Failure (HF), Pneumonia (PN) and Surgical Care Improvement Project (SCIP) is used to measure conformance quality. Following CMS guidelines, only conformance quality that are based on a sample of at least 25 eligible patients were included in our study. The conformance quality for a hospital i with a compliance percentage P_i is given by,

$$C_i = Ln\left[\frac{Pi}{1 - Pi}\right] \tag{1}$$

4.2.3. Experiential quality

This variable measures the quality of interactions between the caregivers and patients as perceived by the patient at a hospital (Chandrasekaran et al., 2012). To calculate this measure six items from the HCAHPS survey were averaged (Q_i) and then a logit transformation applied to the average score. The HCAHPS survey items that are averaged include, (1) How often did doctors communicate well with patients? (2) How often did nurses communicate well with patients? (3) How often did patients receive help quickly from hospital staff? (4) How often did staff explain about medicines before giving them to patients? (5) How often was the patient pain controlled? (6) Were patients given information about what to do during their recovery at home? These measures were developed by CMS and the U.S. Agency for Health care Research and Quality (AHRQ) in 2006. Results are also reported on the CMS Hospital Compare website after being aggregated at the hospital-level and adjusted by CMS for patient characteristics such as education, self-rated health, primary language, age, and service line that are beyond a hospital's control and might affect patients' answers to the survey (www.hcapsonline.org). Following CMS guidelines, only experiential quality based on a sample of more than 100 respondents for HCAHPS scores were included in our study. The experiential quality score for a hospital i with a percentage score Q_i is given by,

$$S_i = Ln\left[\frac{Qi}{1 - Qi}\right] \tag{2}$$

4.3. Independent variables

4.3.1. Classification of HIT systems into bundles

We used a Q-sort method as proposed in Stephenson (1953) to classify 76 HIT into the three categories (Clinical, Augmented Clinical and Administrative HIT). Three experts in the field of Healthcare Information Technology assisted us with the classification. They had an average experience of 7 years and were primarily responsible for implementing HIT systems at a major teaching hospital. They were contacted sequentially and provided with a list of definitions for the HIT systems as provided by HIMSS Analytics and explicit instructions for the sorting exercise. The HIMSS definitions include the roles performed and functionality provided by individual HITs. The classification obtained from the first expert was used as a base and compared with subsequent classifications provided by experts. Differences between the base and the current classification provided by experts were resolved to create a new base classification. A new expert was contacted after every modification to the base classification. The base classification was not shared with the new experts. The process was repeated until we reached a 95% agreement between the modified base classification and the most recent expert classification. The classification process that we used was completed in three iterations. The first expert's classification was used as a base. The classification provided by the second expert had a 68% agreement with the base classification. Dialogues with the first and second experts were then used to modify the base classification and definitions used. The third expert's classification had a 97% agreement with the new base classification. At this stage the remaining items were put in the category that was picked by the majority of the raters to form a new base. The process was terminated at this stage and the base classification at the end of the third iteration was used as the final. One of the experts who had participated in the q-sort process mentioned that the convergence was fairly quick because HIMSS provided clear definitions along with functionality of each HIT included in its database. This largely removed subjectivity in the understanding of the roles of individual HITs. The resulting classification is shown in Table A1. As seen from Table A1, HIT technologies such as accounts payable, cost accounting and budgeting that had very minimal patient centered integration and extent of caregiver interaction are categorized as Administrative HIT. Clinical HIT includes systems like Order Entry and Computerized Tomography that are involved in the collection, testing and processing of patient data for medical purposes or in treating patients. Augmented Clinical HIT systems like Laboratory Information System and Clinical Decision Support integrate different Clinical HIT systems and add decision support and reporting capabilities to the data collected by clinical systems.

4.3.1.1. HIT adoption scores. Hospitals are assigned scores along the three HIT bundles (Clinical, Augmented Clinical and Administrative) based on the Saidin Index (Spetz and Maiuro, 2004; Queenan et al., 2011) of HIT systems in each of these categories respectively.

The Saidin Index is calculated as the weighted sum of the technologies adopted by each hospital where the weights are inversely proportional to the number of hospitals adopting that technology. A Saidin Index assigns a higher weight to rare technologies and hence gives a higher adoption score to hospitals that are front runners in the path towards increased HIT adoption. For instance, in 2008 the Time and Attendance HIT which is commonly used in hospitals was assigned a weight of .11 whereas a CPOE system which was functional only in select hospitals had a weight of .76. This weighing approach will ensure that technologies that are necessity for hospital operations (and hence are implemented by a majority of hospitals) are given lower weights when compared to new and more complex technologies (that are being implemented only by a select group of hospitals). In our sample, the average Saidin index of HIT technologies in each bundles were 5.78 for Clinical (std.dev: 2.85), 4.42 for Augmented Clinical (std. dev: 2.26) and 4.38 for Administrative HIT (std.dev: 2.08).

The Saidin index for each of the three HIT categories is calculated in the following manner,

$$S_{i,t} = \sum_{k=1}^{K} a_{k,t}\tau_{i,k,t} \tag{3}$$

where,

$$a_{k,t} = 1 - \frac{1}{N_t}\sum_{i=1}^{K}\tau_{i,k,t}$$

K = the number of technologies available for each of the three HIT categories
$a_{k,t}$ = The weight assigned to each individual technology
N_t = The number of hospitals under consideration for year t
$\tau_{i,k,t}$ = 1 if technology k is owned by hospital i in year t
= 0 Otherwise

As a robustness test, we also replicated our analyses using count of HIT adoption (Ettlie, 1983; Moch and Morse, 1977; Angst, Devaraj, & D'Arcy, 2012; Burke et al., 2002; Menachemi et al., 2006; Boyer, 1999). The results using count of HIT remain in agreement with the analysis using Saidin index and are shown in Table B1 in Appendix B.

4.4. Control variables

We used a fixed effects estimation approach and hence time invariant hospital level variables (e.g., Ownership structure, Location, etc.) and State level variables (e.g., State Legislations on IT systems) are not included as controls in the model. We controlled for the time variant characteristics such as hospital size, case mix index (CMI) and teaching intensity in this study. The hospital size is measured using the number of beds at the hospital. The teaching intensity derived from the CMS impact files is measured as the ratio of residents to beds at a given hospital. Hospitals with a high teaching intensity score will likely consume more resources due to the need to train medical students and resident physicians (Grosskopf et al., 2001). In addition the involvement of relatively inexperienced medical students and resident physicians in care delivery processes is likely to lead to lower conformance and experiential quality. Case Mix Index (CMI) derived from the CMS impact files is a measure of the severity of illness of the patients admitted at hospitals. It has been shown that hospitals treating more severe patients are likely to use additional resources and have higher operating costs Horn et al. (1985). In addition the increased complexity of operations because of requirements to treat patients with a higher severity of illness is likely to result in lower conformance and experiential quality scores. In addition to the above we also control for Administrative HIT which is measured using a saidin index of Administrative HIT systems. Dummy variables for each year were added in the regression model to control for year effects.

5. Results

Table 1 gives the summary statistics on the key variables used in the analysis. The correlations in Table 1 are determined using Pearson (product-moment) calculations and tests for significance of these pair wise correlations are conducted using the one sided t-test. As seen from Table 1, Clinical HIT and Augmented Clinical HIT are highly correlated ($r = .68$, $p < 0.01$). They also have high standard deviations indicating significant differences in HIT adoption patterns across hospitals. The correlation between the technology bundles and experiential quality is negative ($r_{\text{Augmented Clinical HIT-Experiential quality}} = -.01$, $p < 0.01$; $r_{\text{Clinical HIT-Experiential quality}} = -.02$, $p < 0.01$) whereas their correlations with conformance quality are positive ($r_{\text{Augmented Clinical HIT-Conformance quality}} = .39$, $p < 0.01$; $r_{\text{Clinical HIT- Conformance quality}} = .46$, $p < 0.01$).

5.1. Model estimation to account for endogeneity

A concern while evaluating the impact of HIT on hospital performance is the endogenous nature of the HIT adoption decisions made by the hospitals (McCullough et al., 2010). In particular, HIT adoption decisions may be influenced by a number of institutional, legislative and patient level factors which also impact hospital performance thus leading to endogeneity concerns. As an example, better managed hospitals are likely to have better process quality. These hospitals are also more likely to adopt HIT thus making our estimates of the impact of HIT on process quality biased. To mitigate these concerns we adopted an instrument variable two stage least squares (2SLS) within estimator (fixed effects) for the analysis (Baltagi, 1995; Wooldridge, 2002). Several other studies have used this approach to correct for endogeneity when dealing with data that has similar structures (e.g. Kesavan et al., 2014, Tan and Netessine, 2014; Siebert & Zubanov, 2010). A Durbin-Wu-Hausman test (Davidson and MacKinnon, 1993) which compares the regression estimates for the instrumented and non-instrumented models turns out to be significant for cost ($\chi^2(3) = 109.201$, $p < 0.01$), conformance quality ($\chi^2(3) = 115.458$, $p < 0.01$) and experiential quality ($\chi^2(3) = 22.43$, $p < 0.01$) lending further support to endogeneity concerns. The choice of the within effects estimator (i.e. fixed effects over random effects) was made based on the Hausman test which turned out to be significant ($\chi^2(11) = 1025.86$; $p < 0.01$) providing evidence to reject the null and use the fixed effects model.

We use lagged values of the endogenous variables (Clinical, Augmented Clinical and Administrative HIT) as instruments in our analyses. The approach to use lagged values of the endogenous variables as instruments is a common practice in literature when it is difficult to derive exogenous instruments (Kesavan et al., 2014; Bloom and Van Reenen, 2006, Siebert & Zubanov, 2010, Tan and Netessine, 2014). For example, Kesavan et al. (2014) used linear and quadratic terms of the lagged temporary and part-time labor mix as instruments for the contemporaneous values of these variables. For lagged values of endogenous variables to be valid instruments they must correlated with the contemporaneous values of these variables and be independent of the error terms. Since HITs are expensive to procure and generally have an associated implementation period, it is unlikely for hospitals to drastically change

Table 1
Correlations between variables used in the study.

		Mean	Stdev	1	2	3	4	5	6	7	8	9
1	Conformance quality	2.77	1.096	1								
2	Experiential quality	.909	.278	.10*	1							
3	Cost	13.34	.692	.27**	.02	1						
4	Augmented Clinical HIT	4.42	2.26	.39**	−.01**	.25**	1					
5	Clinical HIT	5.78	2.85	.46**	−.02**	.29**	.68**	1				
6	Administrative HIT	4.38	2.08	.38**	−.04**	.19**	.64**	.57**	1			
7	Beds	211.75	196.95	.32**	−.24**	.16**	.35**	.48**	.35**	1		
8	CMI	1.40	.28	.45**	−.13**	.37**	.33**	.47**	.36**	.63**	1	
9	Teaching Intensity	.063	.157	.10**	−.18**	.24**	.17**	.18**	.14**	.52**	.38**	1

*p < 0.05; **p < 0.01.

Table 2
2SLS fixed effects regression results.

Variables	Cost	Conformance quality	Experiential quality
	Model 1	Model 2	Model 3
Constant	13.81*** (.106)	1.825*** (.113)	.707*** (.024)
Case Mix Index	−.080 (.071)	.513*** (.076)	.076*** (.016)
Teaching Intensity	−.220(.247)	.369(.271)	−.016(.056)
Beds	−.001***(.000)	.000(.000)	0.000(.000)
Administrative HIT	.039**(.016)	.008(.015)	.004(.003)
Year	Yes	Yes	Yes
Augmented Clinical HIT	−.001(.017)	−.000(.015)	−.000(.003)
Clinical HIT	.015(.016)	.047***(.013)	.007**(.003)
Clinical HIT * Augmented Clinical HIT	.003(.003)	.019***(.002)	.004***(.000)
# Observations	13759	14321	14588
Max VIF	10.6	8.5	8.6
R-Squared	.02	.46	.28

*p < 0.1; **p < 0.05; ***p < 0.01.
Instruments for Models 1, 2 and 3: Lags 1 for Administrative HIT, Clinical HIT and Augmented Clinical HIT.

their HIT infrastructure. These high procurement costs and implementation time will ensure that lagged values of our HIT variables are correlated with their contemporaneous values satisfying the first condition. In order to test for the independent of the instruments with the error terms we performed the Arellano-Bond (1991) test for autocorrelation. The test turns out to be insignificant for the cost ($p > 0.1$), conformance quality ($p > 0.1$) and experiential quality ($p > 0.1$) models indicating lags 1 and higher can be used as instruments for the endogenous variables. Based on these tests we use lags 1 of Clinical, Augmented Clinical and Administrative HIT as instruments in our model.[1] As an additional test of the validity of our instruments, we also note that the excluded instruments in the first stage regression models all have F-statistics that are greater than the threshold of 10 (Staiger and Stock, 1994) indicating that they are not weak instruments. All these tests provide confidence in the choice of the instruments.

In addition to endogeneity concerns, our data also suffers from group-wise heteroskedasticity (Greene, 2008) as indicated by the significance ($p < 0.001$) of the modified Wald test (Baum et al., 2000). Given these data considerations, we estimated our models with robust standard errors that accounts for this issue (Wooldridge, 2002). Table 2 gives the results of the 2SLS regression model for cost, conformance quality and experiential quality.

5.2. *Effect of HIT bundles on cost performance*

H1 posits that Augmented Clinical HIT positively moderates the relationship between Clinical HIT and cost performance. That is, the benefits of Clinical HIT on cost performance would increase with increase in Augmented Clinical HIT. Model 1 provides a test of these hypotheses. As seen from Model 1, the interaction term between Clinical and Augmented Clinical HIT is not significant ($\beta = .003$, $p > 0.10$) offering no support to H1. It is also interesting to see that the main effects of both Clinical HIT and Augmented Clinical HIT are not associated with cost performance ($p > 0.10$).

5.3. *Effect of HIT bundles on conformance quality*

H2 suggests a positive moderation of Augmented Clinical HIT on the relationship between Clinical HIT and conformance quality. As seen from Model 2, the interaction between Clinical HIT and Augmented Clinical HIT ($\beta = .019$, $p < 0.01$) is significant and strongly associated with conformance quality, offering support to H2. To better understand the interaction effect, we created a conditional effects plot that illustrates the relationship between Clinical HIT and conformance quality at high (one standard deviation above the mean) and low (one standard deviation below the mean) levels of Augmented Clinical HIT. Fig. 2 represents this plot[2]. As seen from Fig. 2, as Clinical HIT increases, conformance quality increases for hospitals with high Augmented Clinical HIT, while it remains unchanged for hospitals with Low Augmented Clinical HIT. As an illustration, consider hospital (Hospital X) that currently has a mean score on number of beds (Beds = 211.75). If Hospital X has high Augmented Clinical HIT it will show about 2.8% improvement in compliance percentage (P_i) as its Clinical HIT increases from low (one standard deviation below the mean) to high (one standard deviation above the mean). On the other hand if this hospital has low Augmented Clinical HIT it will only show about .1% increase

[1] Our robustness tests involve alternate model specifications with different lag structures which are explained later in the paper.

[2] Note: indicated percentage values in the figure are transformed compliance percentage values.

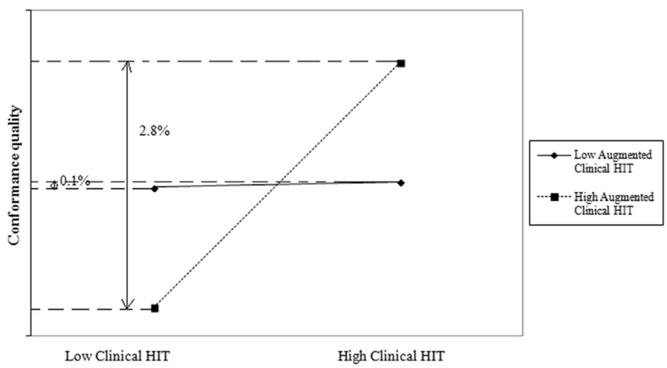


Fig. 2. Two way interaction plot between Clinical HIT and Augmented Clinical HIT for conformance quality.[2]

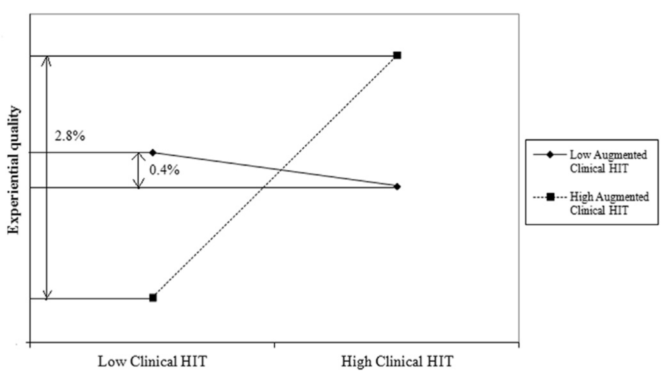


Fig. 3. Two way interaction plot between Clinical HIT and Augmented Clinical HIT for experiential quality.[2]

(non-significant) in compliance percentage (P_i) as its Clinical HIT increases from low (one standard deviation below the mean) to high (one standard deviation above the mean). This suggests that the benefits from Clinical HIT on conformance quality exist under the presence of Augmented Clinical HIT.

5.4. Effect of HIT bundles on experiential quality

H3 suggests that the benefits from Clinical HIT on experiential quality will be offset by counter-productive effects of Augmented Clinical HIT. Model 3 provides a test of this hypothesis. As seen from Model 3, the interaction term between Clinical and Augmented Clinical HIT is significant ($\beta = .004$, $p < 0.01$) and strongly associated with experiential quality. This result runs counter to our hypothesis, offering no support to H3.

To better understand this interaction effect, we created a conditional effects plot that illustrates the relationship between Clinical HIT and experiential quality at high and low levels of Augmented Clinical HIT. Fig. 3 represents this plot. As seen from Fig. 3, as Clinical HIT increases, experiential quality increases for hospitals with high Augmented Clinical HIT, while it is unchanged at Low Augmented Clinical HIT. As an illustration, consider Hospital X from our earlier analyses. If this hospital has high Augmented Clinical HIT it will show about 2.8% improvement in their patient experience scores (Q_i) as its Clinical HIT increases from low to high. On the other hand if this hospital has low Augmented Clinical HIT it will only show about .4% decrease (non-significant) in their patient experience scores (Q_i) as its Clinical HIT increases from low to high. Once again, we find that the effect of Clinical HIT on experiential quality exists only under the presence of Augmented Clinical HIT.

A couple of facts become evident from our analyses. First, the interaction plots clearly demonstrate that complementarities between Clinical and Augmented Clinical HITs for process quality outcomes are only observed for high levels of Augmented Clinical HIT. No impact is observed for low levels of Augmented Clinical HIT. This indicates that high levels of Augmented Clinical HIT are a necessity to realize complementarities with Clinical HIT. Second, only H2 is supported from our analyses. H3 on the negative moderation of Augmented Clinical HIT on the relationship between Clinical HIT and experiential quality is directionally opposite to that argued in the hypothesis. This may be an indication that hospitals have started realizing the benefits of Augmented Clinical HIT and the adjustment period for caregivers which was attributed as the primary reason for the dip in experiential quality may not be as severe as anticipated. Although there is some plausible explanation for the opposite effects for H3, the fact that we do not find support for H1 is surprising. H1 argues for a positive moderation of Augmented Clinical HIT on the relationship between Clinical HIT and cost. The insignificant interaction term and the main effects for Clinical and Augmented Clinical HIT is difficult to explain considering the high cost of adopting Augmented Clinical HIT and the positive complementarities observed for conformance and experiential quality (which should also translate into complementarities for cost). It is possible that subsets of Augmented Clinical HIT may have opposing effects on cost thus leading to insignificant results. For instance, in recent years, hospitals have placed increased emphasis on adopting EMR technologies, which are a subset of Augmented Clinical HIT, due to regulatory pressures (e.g. Passage of HITECH act in 2009). Perhaps, unbundling EMR from the remaining Augmented Clinical HIT can offer more clarity to our hypotheses. To get a better understanding of these relationships, we conducted the following post-hoc analyses.

5.5. Post-hoc analyses

Our analyses show that complementarity exist between Clinical HIT and Augmented Clinical HIT with respect to process quality measures but not with respect to cost. To gain a better understanding on the lack of relationship with respect to cost outcomes, we looked at the technologies within these HIT bundles. Technologies that constitute Clinical HIT are not new to hospitals and in most cases users of these technologies (highly specialized and trained technicians and in some cases nurses and physicians) are trained in their use as a part of their medical education. Thus the learning curve or resistance to using these technologies can be minimal. Augmented Clinical HIT on the other hand has been recently given a lot of attention. Specifically, the passing of HITECH Act has created a lot of focus on the Electronic Medical Record (EMR) technologies given the large stimulus offered to the hospitals. EMR HITs form the basic set of technologies that are required for linking patient records and functionality across the hospital (Elson and Connelly, 1995) and have been the primary focus for HIT adoption following the HITECH Act. We use the EMR Adoption Model proposed by Furukawa et al. (2010) to determine the technologies to be included as a part of EMR technologies. According to Furukawa et al. (2010), the following eight technologies constitute EMRs: pharmacy information system, laboratory information system, radiology information system, clinical data repository (CDR), nursing documentation, electronic medication administration records (EMAR), clinical decision support (CDS) and computerized physician order entry (CPOE). All the remaining Augmented Clinical HITs add additional reporting, integrative and decision support functionality to the basic infrastructure provided by the EMR technologies and are classified as non-EMR HITs.

Given the increased emphasis on EMR HIT following the HITECH Act, the post-hoc analysis intends to parse out the differential impacts of EMR and non-EMR HIT on the relationship between Clinical HIT and hospital performance. The results for the 2SLS regression model for cost, conformance quality and experiential quality are presented in Models 4, 5 and 6 in Table 3.

Results in Table 3 provide interesting insights. As seen from Model 4, the interaction between Clinical HIT and EMR HIT is significant and strongly associated with cost ($\beta = .051$, $p < 0.01$) while the interaction between Clinical HIT and non-EMR HIT significant and negatively associated with cost ($\beta = -.017$, $p < 0.05$). This indicates that EMR and Clinical HIT have negative synergies for cost, i.e., as a hospital increases its EMR and Clinical HIT its cost increases while the reverse is seen for non-EMR technologies, thus canceling each other out in our main analyses. A possible explanation for this result could be the high training and adaptation costs associated with EMR adoption. Since non-EMR HITs build on top of the basic functionality provided by EMRs they may benefit from the knowledge acquired through the EMR adoption. To better understand these interaction effects, we created a conditional effects plot that illustrates the relationship between Clinical HIT and cost at high and low levels of EMR and non-EMR HITs. Figs. 4 and 5 represents this plot. As seen from Fig. 4, as Clinical HIT increases, cost increases for hospitals with high EMR HIT, while it decreases for hospitals with Low EMR HIT. As an illustration, consider Hospital X from our earlier analyses. If this hospital has high EMR HIT it will show about 2.4% increase in cost as its Clinical HIT increases from low to high. On the other hand if this hospital has low EMR HIT it will show about 1.4% decrease in cost as its Clinical HIT increases from low to high. The reverse effect is seen for non-EMR HITs (Fig. 5) with hospitals having high non-EMR HIT showing about .7% reduction in cost as its Clinical HIT increases from low to high while hospital with low non-EMR HIT showing about 1.7% increase in cost as its Clinical HIT increases from low to high. These opposite impacts of EMR and non-EMR HITs on the relationship between Clinical HIT and cost may be the reason for the insignificant cost model in the main analysis.

For conformance quality the synergies between Augmented Clinical and Clinical HIT observed in the main analysis seems to be driven by EMR HITs. As seen from Model 5, the interaction between Clinical and EMR technologies is significant and strongly associated with conformance quality ($\beta = .049$, $p < 0.01$). On the other hand non-EMR HITs are not associated with conformance quality. To better understand these interaction effects, we created a conditional effects plot that illustrates the relationship between Clinical HIT and conformance quality at high and low levels of EMR HITs. Fig. 6 represents these plots. As seen from Fig. 6, as Clinical HIT increases, conformance quality increases for hospitals with high

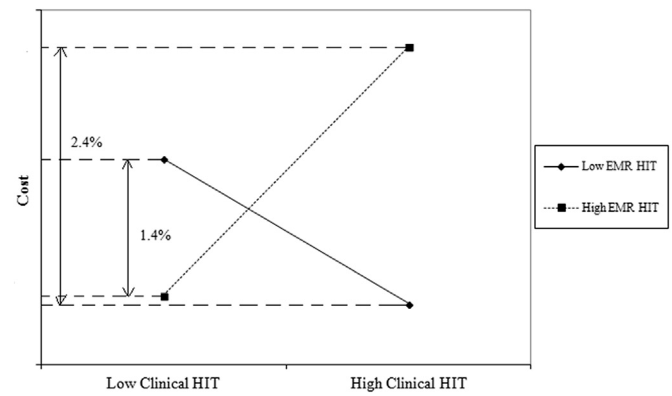


Fig. 4. Two way interaction plot between Clinical HIT and EMR HIT for cost.

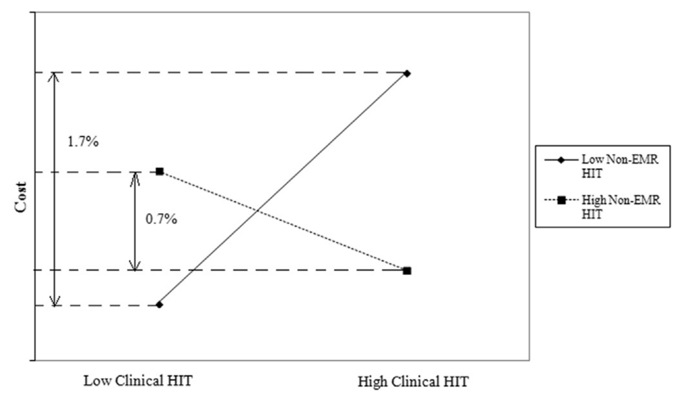


Fig. 5. Two way interaction plot between Clinical HIT and non-EMR HIT for cost.

EMR HIT, while it remains unchanged for hospitals with Low EMR HIT. As an illustration, if Hospital X has high EMR HIT it will show about 2.4% improvement in compliance percentage (P_i) as its Clinical HIT increases from low to high. On the other hand if this hospital has low non-EMR HIT it will show about .1% decrease (non-significant) in compliance percentage (P_i) as its Clinical HIT increases from low to high.

For experiential quality, the impact of EMR and non-EMR HITs are in agreement with the observations from the main analysis. As seen from Model 6, the main effect of EMR HIT is significant and strongly associated with experiential quality ($\beta = .039$, $p < 0.01$) while there is no interaction effect with Clinical HIT. This suggests

Table 3
Post-hoc Analysis Results using 2SLS fixed effects regression.

Variables	Cost	Conformance quality	Experiential quality
	Model 4	Model 5	Model 6
Constant	13.807*** (.107)	1.876***(.114)	.710***(.025)
Case Mix Index	−.085(.072)	.480***(.076)	.070***(.016)
Teaching Intensity	−.234(.250)	.346(.272)	.001(.057)
Beds	−.002***(.0000	.000(.000)	.000(.000)
Administrative HIT	.038**(.016)	.012(.015)	.007**(.003)
Year	Yes	Yes	Yes
Non-EMR HIT	−.010(.032)	.030(.027)	−.019***(.006)
EMR HIT	.044(.047)	.002***(.042)	.039***(.009)
Clinical HIT	.011(.015)	.038(.013)	.007**(.003)
Clinical HIT * EMR HIT	.051***(.017)	.049***(.015)	.004(.003)
Clinical HIT * Non-EMR HIT	−.017**(.008)	.007(.007)	.004***(.001)
# Observations	13793	14267	14525
Max VIF	10.5	8.6	8.8
R-Squared	.05	.46	.25

*p < 0.1; **p < 0.05; ***p < 0.01.
Instruments for Models 4, 5 and 6: Lag 1 for Administrative HIT, Clinical HIT, EMR and non-EMR HIT.

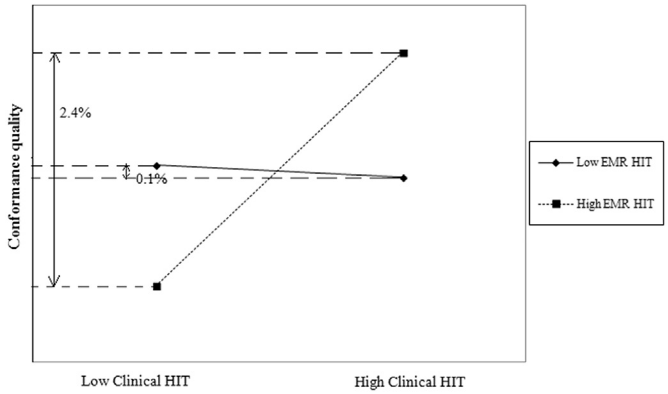
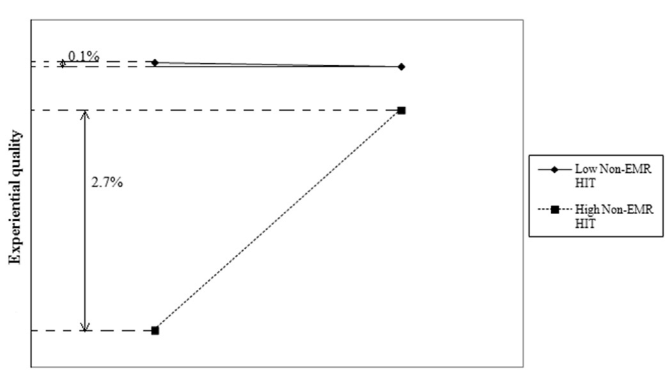


Fig. 6. Two way interaction plot between Clinical HIT and EMR HIT for conformance quality.[2]

that EMR HITs are associated with experiential quality independent of Clinical HIT. The main effect of non-EMR HIT is negative and strongly associated with experiential quality ($\beta = -.019$, $p < 0.01$) while its interaction term is positive and significant (.004, $p < 0.01$), suggesting complementarities with Clinical HIT. To better understand the interaction effect, we created a conditional effects plot that illustrates the relationship between Clinical HIT and experiential quality at high and low levels of non-EMR HITs. Fig. 7 represents these plots. As seen from Fig. 7, as Clinical HIT increases, experiential quality increases for hospitals with high non-EMR HIT, while it remains unchanged for hospitals with low non-EMR HIT. As an illustration, Hospital X with high non-EMR HIT will demonstrate about 2.7% improvement in their patient experience scores (Q_i) as its Clinical HIT increases from low to high. On the other hand if this hospital has low non-EMR HIT it will demonstrate about .1% decrease (non-significant) in their patient experience scores (Q_i) as its Clinical HIT increases from low to high.

The post-hoc analyses offer additional insights on the complex relationship between Clinical and Augmented Clinical HITs. For instance, we find that EMR HITs which constitute an important part of Augmented Clinical HITs have a direct positive association with experiential quality. They show complementarities with Clinical HITs for conformance quality while negative synergies are observed for cost performance. On the other hand non-EMR HITs exhibit complementarities with Clinical HITs with respect to cost and experiential quality while they are not associated with conformance quality. Thus, this post-hoc analysis clearly demonstrates that although EMR HITs are expensive to adopt they are useful in improving process quality outcomes. This suggests a cost-quality



[2]Note: indicated percentage values in the figure are transformed compliance percentage values

Fig. 7. Two way interaction plot between Clinical HIT and non-EMR HIT for experiential quality.[2]

tradeoffs experienced by hospital administrators when implementing HITs in recent years. Furthermore, non-EMR gain from the knowledge acquired during EMR adoptions which may explain its complementarities with Clinical HIT with respect to cost performance. Finally, we find additional support for the observation in the main analysis that the complementarities with Clinical HIT for process quality measures are only observed for high levels of Augmented Clinical HITs (EMR and non-EMR) with no impact seen at low levels. Thus the resources and effort expended by hospitals in adoption of Augmented Clinical HIT will prove to be beneficial directly and through complementarities with Clinical HIT once they achieve high levels of HIT adoption.

5.6. Robustness checks

We performed several additional analyses to demonstrate the robustness of our results which are reported in Appendix B. First, we used a different approach to operationalize our independent variables. Specifically, we measured HIT bundles for Clinical, Augmented Clinical and Administrative HIT using the count of technologies instead of Saidin Index. The count of technologies as a measure of HIT adoption has been used in a number of studies (Ettlie, 1983; Moch and Morse, 1977; Angst, Devaraj, & D'Arcy, 2012; Burke et al., 2002; Menachemi et al., 2006; Boyer, 1999). For example, Angst, Devaraj, & D'Arcy (2012) measured the Clinical and Administrative HIT bundles based on count of technologies from the HIMSS database. The 2SLS regression results using the count of HITs are shown in Table B1. The magnitudes are slightly lower than the Saidin index measures. This can be due to the equal weights applied to all technologies (while Saidin index has higher weights for rare technologies). In general, the results are in agreement with the main analyses.

Second, to minimize concerns that our results are susceptible to different choices of instruments, we repeated the analyses using different lags for the endogenous variables (Lags 1 and 2 instead of Lags 1). Results from this analysis are once again in agreement with the ones reported in Table 2 minimizing concerns on the instrument choice (See Table B3).

Third, we tested a cost model with experiential and conformance quality as predictors in accordance with recent research findings (Senot et al., 2015). That is, both conformance and experiential quality are used in the cost models along with the HIT predictors. The results of this model are shown in Table B3 and are in agreement with the results in Table 2.

Finally, we also present the results from a simpler estimation model – i.e. the results of a fixed effects regression model without accounting for endogeneity (see Table B4). The interaction results are similar to the ones from the main analyses while the main effects of Augmented Clinical HIT are significant without using instruments for conformance and experiential quality. This can be due to the large standards errors obtained using instruments (while these errors are very small using the simple fixed effects as seen in Table B4). All these additional tests and alternative model results hopefully improves the transparency and validity of our results.

6. Discussion and conclusion

6.1. Implications for theory

This study makes several contributions to the literature. First, we address the limitations in the extant literature and argue for the importance of looking at HIT in terms of both patient centered integration as well as caregiver interaction. Most of the existing research has categorized HIT based on functionality (Angst et al., 2012; Burke et al., 2002; Menachemi et al., 2006). Although these studies are advancing our knowledge on the performance benefits from HIT by acknowledging the complementarities between multiple technologies, they fail to account for the two different types of data handled by hospitals (administrative vs. patient) and the critical interactions of HITs with caregivers – i.e., physicians and nurses who are responsible for the delivery of care. Employing insights from the AMT literature (Meredith, 1987; Boyer, 1999), we argue that HIT adoption patterns can be better understood based on the integration of multiple technologies as well as recognition of the critical importance of human capital. Fig. 1 represents the approach used in this study to categorize HIT bundles based on two dimensions, namely the level of patient-centered integration and caregiver interaction. This allowed us to differentiate HIT systems into three distinct bundles – Administrative HIT, Clinical HIT and Augmented Clinical HIT. More importantly, it allowed us to differentiate between Clinical HIT and Augmented Clinical HIT that have varying levels of caregiver interactions. We believe that using a portfolio approach to HIT adoption allows us to understand the differential effects of HIT bundles on hospital performance outcomes.

Second, this study looks at the intermediate performance measures (like conformance and experiential quality) instead of end performance measures (like mortality and readmissions) when evaluating the impact of HITs on performance. End performance such as mortality and readmissions are affected by several diagnosis-related group (DRG) characteristics (DesHarnais et al., 1990) as well as process quality outcomes (Senot et al., 2015; Angst et al., 2012). Thus HIT likely is one among a multitude of factors that impact such high level outcomes. Researchers studying the impact of HIT on end performance may have found mixed results due to the inability to control for these factors. We urge scholars studying HIT adoption to rather focus on process quality outcomes which are increasingly becoming important in terms of reimbursement programs.

Third, this study reveals the presence of complementarities between Clinical and Augmented Clinical HIT with respect to process quality outcomes. That is at higher levels of Augmented Clinical HIT, increase in Clinical HIT is associated with increase in both conformance and experiential quality. No complementarities or tradeoffs are observed at lower levels of Augmented Clinical HIT. When Augmented Clinical HIT is broken down into EMR and non-EMR, we still find similar benefits from these technologies with respect to process quality outcomes. This an important finding for hospitals which need to show simultaneous improvements in both conformance and experiential quality failing which they risk losing as much as 2% of their Medicare reimbursements beginning 2013. Thus investments in Clinical and Augmented Clinical HIT (both EMR and non-EMR) can provide an option for hospitals to achieve simultaneous improvements in both conformance and experiential quality.

Finally, the post-hoc analysis reveals that EMR and non-EMR HITs have different effects on hospitals cost performance. In particular, implementing EMR HITs with Clinical HITs are associated with increased operating cost while implementing non-EMR HITs with Clinical HIT are associated with reduction in operating cost, hence canceling out each other in the main analyses. The negative synergies of EMR HITs and Clinical HIT can be due to the need for additional training and adaptation required when implementing these technologies together. We also find that EMR HIT and non-EMR HITs differently affect process quality outcomes. While EMR HIT has a direct association with experiential quality and complementarities with Clinical HIT for conformance quality, non-EMR HITs affect experiential quality in the presence of Clinical HIT and have no association with conformance quality. Taken together, these post-hoc results offer preliminary evidence on the additional granularity required when investigating Augmented Clinical HIT bundle.

6.2. Implications for practice

Practitioners can benefit from insights on the relationship of Clinical and Augmented Clinical HIT bundles with process quality and cost outcomes. We find complementarities between Clinical and Augmented Clinical HITs when it comes to process quality outcomes. Recent changes in reimbursement policies due to value-based purchasing require hospitals to demonstrate simultaneous improvements along both conformance and experiential quality. Our results suggest that investments in both Augmented Clinical HIT and Clinical HIT simultaneously may help hospitals achieve this goal. The post-hoc analysis further demonstrates benefits from investing in both EMR and non-EMR HITs in improving hospital process quality outcomes but EMR HITs in particular are associated with increase in operating cost. This finding indicates that hospital administrators should not be discouraged with upfront investments in adopting Augmented Clinical HITs (especially EMR) given its association with process quality outcomes. Further, this study demonstrates complementarities amongst different types of technologies. Thus, the answer in realizing the true benefits of technology may lie in adopting technologies in bundles and integrating individual technologies. Similar findings are echoed from the AMT literature where Meredith (1987) wrote that the true benefits of technology only emerge when "separate islands of automation" begin to merge or integrate.

6.3. Limitations & conclusions

We acknowledge the following limitations in the study design which may suggest potential for subsequent research. First, the analysis conducted in this research controls for hospital level fixed effects. We do not control for patient or caregiver level factors that may impact the dependent variables used in the study. Second, the measures of conformance and experiential quality are based on measures used in CMS and HCAPHS survey which only represents a subset of all the initiatives implemented at hospitals. Third, we are unable to differentiate between the availability of technology and the actual usage of technology by the caregivers. Finally, we acknowledge that out measures of HIT adoption (Saidin index or count) are unable to capture different characteristics of individual HITs. An index that incorporates aspects like complexity, usability, actual use, etc will provide a more robust operationalization of HIT adoption. Future research should attempt to mitigate the above limitations and deepen our understanding of the relationship between the proposed technology bundles and hospital performance.

We also acknowledge that there might be potential sources of uncontrolled endogeneity in our empirical strategy. Although, we have made the best possible effort to control for all sources of inconsistency in our estimates, we are aware that no estimation procedure will be perfect, and as such, while we believe in the robustness of our results, we do not rule out that future studies might find differences with respect to our results. We are confident that our results are the most accurate we could obtain given the nature of the empirical data we have collected.

Overall, this study provides important insights for theory and practice. The novel approach to classifying HIT based on functionality and degree of caregiver interaction, the findings of complementarities amongst HIT bundles, and demonstration of the differential impacts of EMR and non-EMR HITs are the primary contributions of this study. These contributions should go a long way to better our understanding of the relationship between HIT and hospital performance and help resolve the mixed research findings on the benefits of HIT adoption.

Appendix A

Table A1
Expert's Classification of HIT Technologies.

Clinical HIT	Augmented clinical HIT	Administrative HIT
Cardiology – Cath Lab	Cardiology Information System	Personnel Management
Cardiology – CT (Computerized Tomography)	Emergency Department Information System (EDIS)	Benefits Administration
Cardiology – Echocardiology	Obstetrical Systems (Labor and Delivery)	Time and Attendance
Cardiology – Intravascular Ultrasound	Radiology Information System	Enterprise Resource Planning
Cardiology – Nuclear Cardiology	Respiratory Care Information System	Telemedicine – Radiology
Intensive Care/Medical Surgical	Clinical Decision Support	RFID – Patient Tracking
Operating Room (Surgery) – Peri-Operative	Nursing Documentation	RFID – Supply Tracking
Operating Room (Surgery) – Post-Operative	Computerized Practitioner Order Entry (CPOE)	Business Intelligence
Operating Room (Surgery) – Pre-Operative	Physician Documentation	Financial Modeling
Clinical Data Repository	Microbiology	General Ledger
Order Entry (Includes Order Communications)	Encoder	Accounts Payable
Blood Bank	Laboratory Information System	Budgeting
Anatomical Pathology	Nurse Acuity	Cost Accounting
Chart Deficiency	Nurse Staffing/Scheduling	Data Warehousing/Mining – Financial
In-House Transcription	Pharmacy Management System	Executive Information System
Radiology – Angiography	Electronic Medication Administration Record (EMAR)	Abstracting
Radiology – CR (Computed Radiography)	Electronic Data Interchange (EDI)	Payroll
Radiology – CT (Computerized Tomography)	Case Mix Management	Materials Management
Radiology – DF (Digital Fluoroscopy)	Data Warehousing/Mining – Clinical	Patient Billing
Radiology – Digital Mammography		Patient Scheduling
Radiology – DR (Digital Radiography)		Credit/Collections
Radiology – MRI (Magnetic Resonance Imaging)		Staff Scheduling
Radiology – Nuclear Medicine		ADT/Registration
Radiology – US (Ultrasound)		OR Scheduling
Outcomes and Quality Management		Interface Engines
Radiology – Orthopedic		DBMS
		Browser
		Web Development Tool
		Email
		Consumer Portal
		Single Sign-On

Table A2
Review of Studies on HIT performance.

Paper	HIT measures	Data type	Performance measures	Outcome	Limitations
Devaraj & Kohli. (2000)	IT Labor, Decision Support System Investments	Primary data from 8 hospitals.	Revenue, Mortality and Satisfaction.	HIT use leads to improved hospital performance after a time lag.	Small sample size. Focused on a single technology.
Menon, Lee, & Eldenburg. (2000)	IT Capital, Medical IT Capital, IT labor	1976-94 data from the Washington State Department of Health	Cost	IT Capital, IT Labor and Medical IT Capital are positively associated with cost	Restricted to financial metrics. Only 86 hospitals from a single state used in the analysis.
Devaraj & Kohli. (2003)	Reports, Disk Input-Output, Central Processing Unit time	Primary data from 8 hospitals.	Revenue/admission, Mortality and Revenue/day.	HIT usage leads to improved hospital performance.	Small sample size.
Koppel et al. (2005)	CPOE	Data from a 2002–2004 survey of 261 hospitals.	prescription error risks	Use of CPOE facilitated 22 types of medication error risks	Cross-sectional data. Small sample size. Single technology and performance measure.
Kucher et al. (2005)	Computer alert system.	2500 patients from a single hospital	Rates of deep-vein thrombosis and pulmonary embolism	Use of the computer alert program reduced the rate of deep-vein thrombosis and pulmonary embolism.	Cross sectional data from a single hospital. Single Clinical HIT tested in a controlled setting. Use of a single performance measure.
Menachemi et al. (2006)	Clinical HIT, Administrative HIT, Strategic HIT	HIMSS, Primary data	Financial Performance	Increased HIT use is associated with higher revenues, cash flows, etc although it also leads to increased cost.	No quality of care measures used in the analysis. Classification of technologies based on functionality only.
Linder et al. (2007)	Electronic health records (EMR)	Data from a 2003–2004 survey.	17 ambulatory quality indicators	Use of EMR is not associated with improvements in quality of ambulatory care.	Cross-sectional analysis. Focus on a single HIT.
Angst et al. (2010)	Individual hospital information technologies for Cardiology	HIMSS	Cost per patient, Length of Stay	Sequence of adoption of information technology impacts hospital cost and length of stay	Focused only on Clinical technologies specific to the Cardiology department.

Table A2 (*continued*)

Paper	HIT measures	Data type	Performance measures	Outcome	Limitations
DesRoches et al. (2010)	Electronic Health Records (EMR) Usage	Cross sectional data on 2952 hospitals for the year 2008	Mortality, length of stay, readmission and cost	EMR use is not associated with improvements in hospital cost and quality.	Cross sectional data. Focus on EMR usage without accounting for interactions amongst technologies.
McCullough et al. (2010)	CPOE Use	HIMSS and CMS data from 2004 to 07	CMS Process of Care Measures	CPOE is associated with improvements in two pneumonia quality measures	Focused on a single technology. Only process of care measures used to evaluate performance.
Aron et al. (2011)	Automation of sensing, control and monitoring systems	Incremental automation and error data from two hospitals	Procedural error rates, Interpretative error rates	Automation of the core error prevention functions helps in reducing medical errors.	Only looks at automation of error prevention functions. Small sample size of two hospitals.
Queenan et al. (2011)	CPOE Use, Hospitals HIT infrastructure	HIMSS, HCAHPS	Patient Satisfaction.	CPOE use increases patient satisfaction. This effect is stronger non-Academic hospitals	Focused on a single technology. Outcome measure can be impacted by hospital, patient and caregiver level factors.
Angst, Devaraj & D'Arcy (2012)	Cardiology HIT, Administrative HIT	HIMSS, CMS, HCAHPS	Technical Protocols of Patient Care, Interpersonal Care, Mortality, Patient Loyalty, Patient Overall Rating	Administrative HIT affects Interpersonal Care. Cardiology HIT affects Technical Protocols of Patient Care.	Restricted to Cardiology department. Classification of HIT based only on functionality.

Appendix B. Robustness checks

Table B1
2SLS fixed effects regression results using HIT count as a measure of adoption.

Variables	Cost	Conformance quality	Experiential quality
	Model B1	Model B2	Model B3
Constant	13.680*** (.128)	1.695*** (.142)	.674***(.031)
Case mix index	−.029 (.081)	.529***(.097)	.093***(.021)
Teaching intensity	−.322(.265)	.522(.337)	−.052(.073)
Beds	−.002*** (.000)	.000 (.000)	−.000 (.000)
Administrative HIT	.016 (.020)	−.008 (.013)	.007** (.003)
Year	Yes	Yes	Yes
Augmented Clinical HIT	.034 (.041)	−.009 (.016)	−.004 (.003)
Clinical HIT	.018 (.017)	.025* (.012)	.005* (.003)
Clinical HIT * Augmented Clinical HIT	.000 (.000)	.012*** (.001)	.001*** (.000)
# Observations	13759	14321	14588
Max VIF	9.5	7.4	7.6
R-Squared	.07	.20	.22

*p < 0.1; **p < 0.05; ***p < 0.01.
Instruments for Models B1, B2 and B3: Lags 1 for Administrative HIT, Clinical HIT and Augmented Clinical HIT.

Table B2
2SLS fixed effects model using Lags 1 and 2 of the endogenous variables as instruments.

Variables	Cost	Conformance quality	Experiential quality
	Model B4	Model B5	Model B6
Constant	13.85*** (.117)	2.39*** (.126)	.833*** (.026)
Case mix index	−.077 (.078)	.168** (.084)	.014 (.017)
Teaching intensity	−.100 (.261)	.011 (.289)	.025 (.057)
Beds	−.001*** (.000)	−.000 (.000)	−.000 (.000)
Administrative HIT	.022 (.024)	−.018 (.023)	−.005 (.005)
Year	Yes	Yes	Yes
Augmented Clinical HIT	−.012 (.020)	−.006 (.021)	−.005 (.004)
Clinical HIT	.003 (.019)	.025 (.018)	.005* (.004)
Clinical HIT * Augmented Clinical HIT	.006 (.004)	.012*** (.004)	.005*** (.001)
# Observations	11759	11263	11547
R-Squared	.01	.53	.24

*p < 0.1; **p < 0.05; ***p < 0.01.
Instruments for Models B4, B5 and B6: Lags 1 & 2 for Administrative HIT, Clinical HIT and Augmented Clinical HIT.

Table B3
2SLS fixed effects regression results using conformance quality and experiential quality as predictors for cost.

Variables	Cost
	Model B7
Constant	13.892*** (.117)
Conformance quality	.028*** (.009)
Experiential quality	−.088* (.044)
Case mix index	−.116 (.073)
Teaching intensity	−.313 (.256)
Beds	−.001*** (.000)
Administrative HIT	.029*(.016)
Year	Yes
Augmented clinical HIT	.000(.016)
Clinical HIT	.020(.015)
Clinical HIT * Augmented Clinical HIT	.001(.003)
# Observations	13026
R-Squared	.02

*p < 0.1; **p < 0.05; ***p < 0.01.
Instruments for Model B7: Lags 1 for Administrative HIT, Clinical HIT and Augmented Clinical HIT.

Table B4
Fixed effects regression results using HIT Saidin Index as a measure of adoption.

Variables	Cost	Conformance quality	Experiential quality
	Model B8	Model B9	Model B10
Constant	13.640*** (.079)	1.128***(.092)	.683***(.022)
Case Mix Index	.020(.054)	.643***(.063)	.092***(.015)
Teaching Intensity	−.297(.183)	−.209(.218)	−.086* (.050)
Beds	−.001*** (.000)	.000* (.000)	.000 (.000)
Administrative HIT	.003 (.004)	.010** (.005)	.001 (.001)
Year	Yes	Yes	Yes
Augmented Clinical HIT	.001 (.003)	−.026*** (.004)	−.002** (.001)
Clinical HIT	−.002 (.003)	.022*** (.003)	.003*** (.000)
Clinical HIT * Augmented Clinical HIT	−.001 (.000)	.010*** (.000)	.001*** (.000)
# Observations	16755	17430	16677
Max VIF	9.7	9.6	12.1
R-Squared	.05	.55	.28

*p < 0.1; **p < 0.05; ***p < 0.01.

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