Performance Effects Related to the Sequence of Integration of Healthcare Technologies

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There is a natural order to most events in life: Everything from learning to read to DNA sequences in molecular biology follows some predetermined, structured methodology that has been refined to yield improved results. Likewise, it would seem that firms could benefit by adopting and implementing technologies in some logical way so as to increase their overall performance. In this study of 555 hospitals, we investigate the order in which medical technologies are transformed into information technologies through a process of converting them from stand-alone technologies to interoperable, integrated information systems and whether certain configurations of sequences of integration yield additional value. We find that sequence does matter and that hospitals that integrated foundational technologies first—which in this case are known to be more complex—tend to perform better. Theoretical and practical implications of this finding and others are discussed.

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1. Introduction

Service industries invest heavily in information technology (IT) in order to improve delivery of service (Froehle and Roth 2007). The healthcare industry is no exception—in 2007 the healthcare industry invested more than US$172 billion in technology and almost US$7 billion in IT (Dixon 2007). Not dissimilar to other sectors, the healthcare industry struggles to quantify how, or if, these investments improve service delivery—either through reduced cost of care or improved quality of care. These increases in investment and use of technology call for a better understanding of the management of technology, described as "how to develop, adapt and exploit technological capabilities to create new or improved products or services to accomplish the strategic goals of an organization" (Gaimon 2008). In this study, we investigate how the process of technology adoption and integration impacts both cost and quality in the healthcare setting.

Because the use of technology, and more specifically IT, in the healthcare setting is relatively new compared with other industries such as financial services, air travel, or retailing, studies of healthcare technology and value are sparse. Researchers from a wide range of disciplines have attempted to discover what relationships, if any, exist between capital expenditures for technology adoption and business value. Some examples within the operations management

(OM) field exploring technology and value include manufacturing flexibility (Anand and Ward 2004, Gaimon and Morton 2005), computer-integrated manufacturing technology (Groover 2008), and enterprise resource planning (ERP) systems (Hendricks et al. 2007). This direct link between technology adoption and value has been held to scrutiny in the operations, information systems (IS), and management disciplines to the extent that the literature has noted a "productivity paradox" (Brynjolfsson 1993) such that technology is shown in some studies to have no effect on performance. This paradox has, in large part, been challenged and discredited, but not without considerable debate. The consensus now suggests that the link between technology and performance is more nuanced and the methods used for measurement are vitally important (Brynjolfsson and Hitt 1996, Devaraj and Kohli 2000, 2003). In this study, we are interested in moving beyond the technology artifact itself and into the process of technology integration. More to the point, most technology–value research in some way analyzes performance before and after a technology event such as adoption, investment, or implementation. The challenge associated with this type of analysis is that a technology typically supplants some manual process, thus providing only a comparative result, i.e., "firms that invest in technology perform better than their counterparts that do not." With technology creating new applications and functions that

did not exist in the past, the comparative analysis becomes increasingly less useful. For example, quantifying the financial value of a radio-frequency identification (RFID) system to enhance supply chain management capabilities is difficult because it not only replaces manual inventory tracking, but also enables visibility into the supply chain that was not previously possible (Lee and Ozer 2007). In simple terms, we depart from a traditional view that often operationalizes technology as a tool that can substitute or complement labor and instead argue that the configuration of these technologies will create additional value.

Our goal in this paper is not simply to test and discover correlates of value within the healthcare context, but instead to dissect the technology–process–value link by taking a nuanced approach to the relationship. We will begin by succinctly defining the transition from technology to IT to IS, the absence of which may account for some of the measurement issues in prior studies. This will lead to one of our propositions that value results not solely from the adoption of "technology," but that value intensifies if the technology is transformed into an "IT" by way of integration into an IS. The first research question we are addressing is: Does greater value result when a stand-alone medical technology is integrated into an interoperable health IT?

Next, acknowledging prior research suggesting that measurement is critically important to discovering the link between technology and performance, we depart from traditional measurement methods of counts, investment dollars, or extent of use of technology. Instead, we argue that these quantity-based measures only partially explain variance in performance and that the sequence of integration explains variance above and beyond other indicators. For example, we know that in some cases, firms have implemented the same technologies, yet variance in performance still occurs. We contend not only that the sequence with which technology is transformed into IT is a key indicator of this performance variation, but also that greater distances between sequences will be associated with greater variation in performance. Here, we address the second research question: Does order of integration of medical technologies into an IS matter? If so, what are the best integration sequences, and does the number of integrated technologies impact performance?

2. Background

2.1. Definitions of Technology, IT, and IS
Although definitions for technology abound and these definitions are often context specific (Orlikowski 2007), we offer the following description as proposed by Gaimon; "technology is the embodiment and deployment of technical and scientific knowledge and discoveries that lead to the creation of goods and services," (Gaimon 2008, p. 1). Medical technology, which is a subset of technology used by healthcare providers, has been defined as "principles and techniques providing tools for extending the physician's powers of observation and making more effective his role as a therapist," (Andersen and Newman 1973, p. 100). More simply, medical technologies are used to diagnose, fix, and/or control various medical conditions. The mechanisms through which these technologies accomplish their tasks vary greatly. For example, the types of output range from strip-chart, paper-based output to extensive image storage and retrieval.

We define IT as the hardware, software, telecommunications, database management, and other information processing technologies used in computer-based IS (O'Brien 2002, p. 7). In the healthcare context, IT is often referred to as health information technology (HIT), which has been defined as: "the application of information processing involving both computer hardware and software that deals with the storage, retrieval, sharing, and use of healthcare information, data, and knowledge for communication and decision making," (Thompson and Brailer 2004). The focal technologies in our study are machines that are used in hospitals to diagnose cardiac-related health issues. A medical technology, as described above, becomes an HIT when the data that it once captured in an isolated, stand-alone way become digitized, providing the ability to store, archive, retrieve, and make it interoperable. Many of the medical technologies we are studying have been in existence for 30 or more years, but the *integration* of these technologies is a more recent phenomenon. We suggest that adoption is different than integration primarily because integration suggests a link between what was a stand-alone technology into an information and communication network.

Finally, we define an IS as a set of people, procedures, and resources that collect, transform, and disseminate information in an organization, and a system that accepts data resources as input and processes them into information products as outputs (O'Brien 2002, pp. 14–15). In this definition, HIT is a subset of an IS (see Figure 1).

All three of these variants of technological innovations have been argued to be related to performance in the broad class of research known as business value of technology studies. Yet at a minimum, these varied definitions should provide the basis for our argument that researchers need to succinctly define the type and function of the innovation they are studying so that the relationship to performance is less ambiguous.

Figure 1   Framework Describing Technology Definitions and Relationships
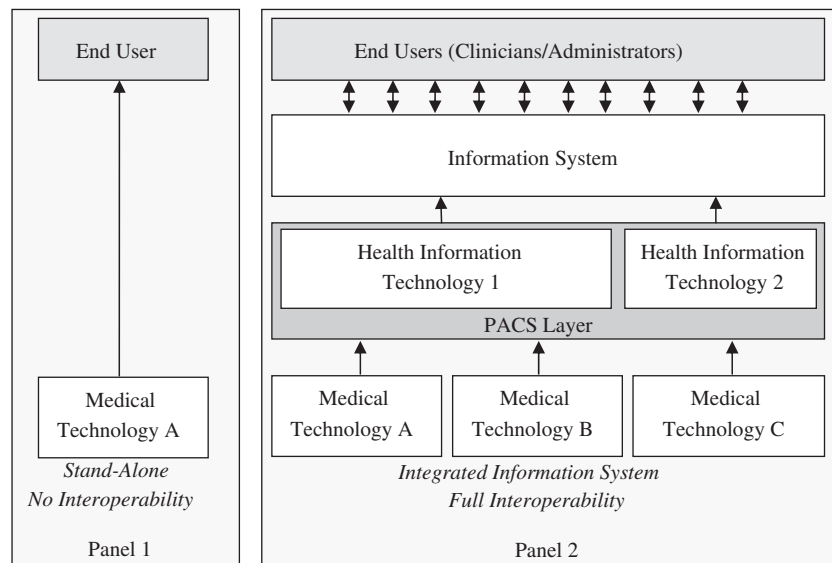
2.2. HIT and Value

We posit that the link between value and the *adoption* of a medical technology is somewhat tenuous, but the link between value and the integration of HIT in the same setting will be stronger. Take, for example, the use of one of the medical technologies—a computed tomography (CT) scan—which is used to diagnose cardiovascular problems; the output of which is a diagnosis-quality image. If this image is not integrated into an interoperable IS within the hospital, its benefits are somewhat limited because it is more difficult for other clinicians, beyond the one responsible for reading and interpreting the image, to access the data (see Figure 1, panel 1). Secondly, the data collected within stand-alone technologies either never make it into a central repository or there is a significant delay, thus limiting its value for real-time decision making. Finally, stand-alone medical technologies typically do not communicate with other technologies so any information generated by one machine will not be useful beyond its intended purpose (e.g., a prescribing system would not feed into the emergency department's database so drug interactions could go undetected).

The benefits of diagnostic results from a medical technology such as a CT scan are not debatable, as demonstrated by numerous clinical trials; instead, we argue that integrating the data from the scan into an IS through an HIT conduit will offer benefits above and beyond the already important diagnostic benefit. If, for example, the CT scan is linked into the hospital Picture Archiving and Communication System (PACS[1]), the image will be stored and easily distributed to multiple parties involved in patient care.

Because of its integration with other hospital systems, it enables more effective and efficient patient care processes through simplified procedures and shared information across traditional functional boundaries within a hospital (van de Wetering et al. 2006). As shown in Figure 1, panel 2, integrating the HITs from the PACS into an IS provides a more comprehensive and collaborative environment to deliver care.

Finally, in Figure 1, panel 2, we also identify an IS layer. The IS layer defines whether or not the hospital has an integrated IS that encompasses the benefits of PACS but also adds full connectivity between HITs plus decision support, alerts, and possibly order entry. Further, the bi-directional arrows suggest that information comes both from the HITs and from people inputting information (such as name, address, notes, diagnosis, etc.). As our study was specifically focused on cardiology departments within hospitals, we sought subject matter experts to further inform our investigation. We conducted interviews with five CIOs of hospitals, as well as several discussions with clinicians and other staff within hospitals. The consensus among them was that the cardiology information system (CIS) is typically the infrastructure under which all of the technologies are integrated within a cardiology unit. In fact, many suggested that the CIS was the "foundational system" under which the entire platform should be developed. We will address this in greater detail below.

3. Theory and Hypothesis Development

In this section, we introduce our research model and subsequently provide justification for each of the

hypotheses we test (see Figure 2). We argue that the number of HITs integrated, the sequence of HIT (i.e., when technologies are integrated), and the distance between sequences (i.e., their similarities) impact performance in hospitals.

As noted, for the purpose of this paper, we argue that a medical technology becomes an HIT when it is made interoperable. Evidence of the value of interoperability has been shown in other domains and includes applications such as computer-integrated manufacturing (CIM) (Dean and Snell 1996) and ERP (Hendricks et al. 2007). With respect to CIM, researchers and practitioners alike have identified the value in integrating stand-alone manufacturing technologies—called "islands of automation" (Fine and Hax 1985)—into a centralized system. As sophistication in the manufacturing environment increased, firms started to link together these islands into an IS and realized value from the ability to view the system holistically. Similar to the interoperability gains in CIM, firms seek an advantage through system interoperability in ERP systems (Gattiker and Goodhue 2005) by coordinating various pieces of information from and to disparate decision makers. Finally, the healthcare literature supports the proposition that hospitals gain efficiencies by integrating technologies within the cardiology function and the primary drivers of these efficiencies are better communication and access to information (Li and Benton 2006, van de Wetering et al. 2006). This discussion leads to the proposition that the value of an IT exceeds the value provided by stand-alone technology. This additional value occurs because of the interoperability and centralized location of information that provides a means for increased task and process efficiency and/or effectiveness. Although hospitals face different conditions than typical manufacturing firms do, research shows that hospital operational failures often occur as a result of communication breakdown between organizational units (Tucker 2004). Thus, hospitals can use IS to coordinate wide-ranging pieces of information and enable better decision-making processes by conveying information across boundaries.

Dewan et al.'s (1998) research supports the proposition that firms with a need for coordination and control across its business units invest more in information processing and IT. The network externalities' literature suggests that if only a few technologies are integrated, users will have only a small amount of information available to them and coordination will be low (Katz and Shapiro 1985). Thus, as more technologies are integrated, more information will be centrally available for a given user to efficiently and effectively complete a task or process. Further, integration enhances the value derived from use of other technologies as it relates to management decision making. Therefore, when decision support at the management level is coupled with the normal benefits of CT use, the effects will be amplified. Malone et al. (1987) have termed this phenomenon an "electronic integration effect" in that the construction of these networks of interoperability enhances information and process sharing across organizational entities. Others have shown that increasing concentrations of technology and complementary systems have positive impacts on performance (Nambisan 2002). Hence, we posit the following:

H1a: As a hospital integrates more medical technologies into a PACS (i.e., transforming them from medical technology to HIT), process *costs* decrease.

H1b: As a hospital integrates more medical technologies into a PACS, process *quality* increases.

We contend that viewing technology as a static entity ignores the HIT artifact itself and minimizes the richness and complexity of the HIT-value link (Orlikowski and Iacono 2001). As the integration of components into an IS evolves over time, its analysis should involve a temporal component instead of the standard "snapshot in time" approach. One method to investigate the temporal aspects of how system components work together is through analyzing the sequence of integration. Use of sequence analysis has been used previously to characterize process variety (Pentland 2003), project management approaches (Sabherwal and Robey 1993), and order of social processes (Abbott 1983). This analysis method allows researchers to describe when an event takes place relative to other events. The absolute moment in time is inconsequential in most applications of sequence analysis as it is the order in which the events occur that is of primary interest. To the extent that some of these medical technologies are more difficult to integrate, we argue that, over time, a more preferred sequence will emerge that streamlines the learning

Figure 2   Research Model
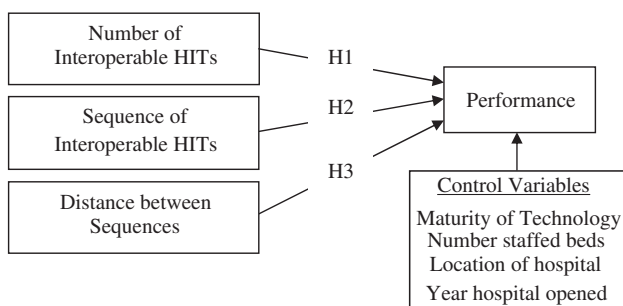
process. While this phenomenon is not new, and has been paraphrased as a "learning to learn" process (Levitt and March 1988), what is novel is its operationalization and measurement. Organizational learning literature suggests that learning procedures will be adopted when they result in favorable outcomes and organizations will continue to use these routines until improvements diminish (Levitt and March 1988). Therefore, if the implementation of medical technology A is successful and learning is high among the users, this knowledge is likely to transfer to the implementation of medical technology B.

We seek to differentiate organizations based on the sequences with which they integrate medical technology into an IS through HIT. Depending on the order of integration, varying amounts of learning will occur yielding heterogeneity in performance above and beyond the effect of the number of technologies within an IS. While learning has been researched broadly and extensively, we focus on the aspect of learning most pertinent to this setting; that is, how sequence impacts learning. Education literature suggests that performance is improved when simple tasks are learned first followed by increasingly complex tasks (e.g., van Merrienboer et al. 2003). In the context of technology, greater complexity of use is associated with greater risk of implementation failure (Premkumar and Roberts 1999). Thus, one would expect simpler technologies to be integrated first. However, we argue that the early implementation of a foundational IS—which in this case is known to be complex—will yield greater gains. This is because a foundational IS will facilitate interoperability by forming the infrastructure on which other applications will interface.

The concept of a foundational IS is also exemplified in two OM frameworks—the sand cone model (Ferdows and DeMeyer 1990) and competitive progression theory (Roth 1996). The sand cone model posits as a firm develops and improves its processes to build in quality, it creates a base knowledge and skill set that enables it to build in other capabilities. A firm could try to develop its capabilities in a different order, however, the literature suggests that those capabilities would not be lasting (Ferdows and DeMeyer 1990). The competitive progression theory builds on the sand cone model by defining the theoretical reasoning and structure around the sand cone model to develop it into a theory. In the competitive progression theory, a firm first develops its processes to build in quality. That knowledge base and skill set enables it to build in cumulative capabilities of reliability, flexibility, and cost efficiency (Rosenzweig and Roth 2004, Roth 1996).

The implementation of a foundational IS creates the knowledge and infrastructure necessary to incorporate other entities into the system and from a technical standpoint, an organization could integrate technologies (e.g., link the HITs within a PACS) without first implementing the foundational IS, yet we contend that greater benefits will result from early implementation. This learning leads to improved processes, which can result in reduced costs and/or improved quality.

A CIS is developed with the intent of linking disparate HITs. Thus, we would expect integration sequences that incorporate a CIS first to be more likely to be interoperable than others. Yet, consistent with contingency theory, we acknowledge that the best sequence for a given organization may vary by organizational structure, goals, and other factors (Drazin and Van De Ven 1985), so there will be multiple "best" sequences. Thus, the order of integration of five medical technologies and the CIS should impact performance in terms of both cost and quality, and we would expect those sequences that enable interoperability to yield better performance, over and above that of sequence length. Therefore we test:

H2a: Technology integration sequences that enable interoperability will outperform other technology integration sequences in terms of process *costs*.

H2b: Technology integration sequences that enable interoperability will outperform other technology integration sequences in terms of process *quality*.

Ideally, firms should integrate technology in a sequence that readily enables interoperability so that the technologies can communicate with each other. However, a sequence that is closer to an interoperable sequence should yield better results than a sequence that ignores interoperability components. The idea of closeness parallels the profile deviation literature in strategy (Venkatraman and Prescott 1990), which advocates comparison between actual profile and "ideal" profile. In their method, actual data are compared with the model and penalized for the "distance" from the ideal. The samples that are closest to the ideal deviate least from the profile, and therefore exhibit better performance. We propose that the less a firm deviates from a best sequence, the better its performance.

H3a: An increasing degree of resemblance to interoperable sequences is associated with decreasing process *costs*.

H3b: An increasing degree of resemblance to interoperable sequences is associated with increasing process *quality*.

4. Methods

We test our proposed hypotheses in a healthcare context, specifically examining cardiology technologies

within US hospitals. The unit of analysis is an individual cardiology department within a hospital. We combine and analyze data collected from two sources. The first is a nationwide, annual survey of care delivery organizations in the United States, conducted by HIMSS Analytics (HA). The HA data provide information about the technologies integrated within a cardiology department and the contract date for integration of those technologies. The second source of data is the American Hospital Directory, which provides both financial and quality data as well as control variable data such as hospital size, urban/rural designation, and hospital age.

We chose to test our hypotheses on technology applications in cardiology for several reasons. First, there are a finite number of technology applications that are typically integrated into a cardiology system, thus providing boundaries for our analysis. Some common medical technologies that can be transformed from stand-alone diagnostic technologies into HIT within a PACS include nuclear cardiology, intravascular ultrasound, CT scanning, echocardiology, (EC) and cardiology catheterization laboratory (CATH). Additionally, these HITs can be integrated with a CIS, which as described earlier is a foundational IS that includes functions such as the collection and distribution of cardiac data from different sources, data storage, management, alerts, decision support, statistical analysis, and other information. The second reason we chose this context is that the order in which cardiology departments adopted technologies varied greatly, allowing for a heterogeneous base of sequences to observe. Third, the academic literature in IT payoff advocates examining performance at the level at which the technology operates rather than extrapolating to higher organizational levels (e.g., Kohli and Devaraj 2003). Finally, we chose to focus on cardiology departments because they exist somewhat ubiquitously throughout the country and their financial and quality results are reported separately from other departments.

From HA, we capture the technologies that are integrated and the contract year the hospital integrated that technology. Our data specifically identify when the medical technology was integrated, not when the technology was adopted (see Appendix A for details). In almost all cases, the stand-alone technology was in place long before it was integrated. From this information, we construct the sequence in which a cardiology department adopted these six (or fewer) technologies into an integrated system. This sequence forms the basic building block of our analysis. Once we calculate the sequence of integration, we compare and contrast the similarities and differences among sequences as well as their relationship to performance.

We have discussed the importance of an analysis including a temporal component instead of a "snapshot in time" approach. We constructed a temporal view of each hospital's sequence by tracking the dates of integration for each medical technology. For example, if a hospital integrated technologies in the following years; Application A in 2003, B in 1992, C in 1990, D in 2002, E in 2001, and F in 2007, we generated and analyzed a chronological temporal pattern with the sequence C-B-E-D-A-F. In addition, a hospital that integrates medical technologies in the following way: A in 2003, B in 1987, C in 1980, D in 1999, E in 1988, and F in 2004 would have the same sequence of implementation (C-B-E-D-A-F) even though the years of integration are different. While technology advancements would suggest that the 1990 Application C is more sophisticated than the 1980 Application C, we are testing whether or not the amount of learning that translates from one integration to the next impacts performance and whether there is something unique about the sequence that translates into performance differences. We do separately examine the effect of the maturity of the technologies by including a variable that measures the years since adoption, but the sequence can be assessed in the absence of this metric. The HA data consisted of 3989 hospitals, and we found 555 hospitals that had integrated at least two cardiology technologies out of a possible total of six. This constitutes our original sample size and makes up approximately 15% of the total number of hospitals in the United States.

4.1. Sequence Comparisons

We compared sequence similarities using a matching algorithm as applied through the ClustalG computer program (Wilson et al. 1999), which is derived from ClustalX, a program for comparing DNA sequences. The software uses dynamic programming to quantitatively compare pairwise sets of sequences and applies a distance metric that describes the level of agreement between the pairs. For example, ClustalG compares the sequence (a) 1-2-3-4 to (b) 1-3-4 and calculates the distance between (a) and (b) by assigning a "cost" for inserting gaps and deleting events. If a digit match were valued at 10 points, a perfect sequence match between two sequences each with a length of four digits would be 40. In the example above, sequence (a) is four digits (events) and (b) is three, therefore the maximum achievable score is 30 points. However, the program also assesses an insertion penalty cost of 1 point (this can also be manually set to a specific value if *a priori* information about the penalty is known), thus the similarity between 1-2-3-4 and 1-3-4 would be 29 points (i.e., maximum score of 30 minus insertion gap of -1 between 1 and 3 in sequence (b); yielding the optimal match relative to

cost of 1-2-3-4 compared with 1-_-3-4. Thus, the greater the similarity, the higher the score.

Previous research has shown the matching algorithm to be a good tool for measuring similarity of sequences in such applications as DNA analysis (Sankoff and Kruskal 1983), social science applications (Abbott 1983), project management (Sabherwal and Robey 1993), and work process variety analysis (Pentland 2003). This algorithm, as applied to our data, compares the integration sequence for every hospital against the integration sequence of every other hospital. Consistent with extant literature in this area (Pentland 2003, Sabherwal and Robey 1993), we assigned weights to each transformation move as follows: a matched item (10.0), inserting a gap (1.0) and deleting an item (1.0). ClustalG examines multiple ways to transform one sequence to another and provides the highest score possible for a particular sequence pair.

Because a hospital may integrate up to six technologies, the maximum score that a comparison pair of hospitals could achieve is 60 points. After all pairs of hospitals have been given a score based on the optimal matching technique, we place them in clusters. This is first done by finding the pairs with the highest score (60 in this case) and grouping them together (see Table 1, panel 1, dashed outline). Hospital 1 (H1) matches hospitals 2 (H2) and 5 (H5) perfectly, thus they form cluster A. These three hospitals are then removed from the selection pool. The next highest match within the table (see panel 2, dashed outline) is hospital 4 and 6, thus forming cluster B. At this point, only hospital 3 is unmatched to a cluster, but it is closer to cluster B than it is to cluster A; a score of 45 vs. 30, respectively (see panel 2, double outline vs. shaded gray) so it is included in cluster B.

This cyclical approach continues by decreasing the score until all hospitals are matched to a cluster or the minimum cutoff score of 40 has been reached. A cutoff score of 40 was used as the threshold for several reasons: (1) there was minimal variation within clusters and sufficient variation across clusters of hospitals;

(2) thresholds lower than 40 resulted in hospitals having similarity scores matching more than one cluster; and (3) thresholds higher than 40 were too stringent because very few hospitals had matches at that level of precision.

4.2. Performance Metrics

We use four separate performance measurements for a given cardiology department: two for cost and two for quality. First we define a term—case mix index (CMI)—that will be used often throughout the remainder of this paper. Hospitals calculate their CMI from the industry-standard diagnosis-related group, which serves as an indicator of the complexity of procedures and the severity of complications within patients. CMI is used to adjust various hospital metrics as a means of normalizing for variations in procedures, patients' overall health, and severity of their illness (Sturgeon 2007). As a comparison, we use both standard metrics and CMI-adjusted metrics within our analysis.

To assess the cost of care, we use the cardiology department's average cost per patient and CMI-adjusted average cost per patient. This is a frequently used financial metric in the healthcare literature (e.g., Bond et al. 1999, Wachter et al. 1998). Beyond financial measures, quality outcomes constitute a key performance metric in healthcare (e.g., McGlynn et al. 2003), but quality in service processes is notoriously difficult to measure (Sampson and Froehle 2006). We operationalize quality through average length of stay (ALOS) of patients and through CMI-adjusted ALOS, both measured specifically within the cardiology department. Often ALOS is used as a measure of efficiency (Glick et al. 2003, McDermott and Stock 2007), but it has also been shown to assess quality as well (e.g., Hwang et al. 2002). The conceptualization of ALOS as quality has been argued from two opposing viewpoints: (1) hospitals may discharge patients early for financially motivated incentives, yielding poorer quality of care (i.e., lower quality yields lower ALOS), or (2) as adverse events occur, healthcare

Table 1   Cluster Formation Example

	H1	H2	H3	H4	H5	H6
H1	–	60	30	35	60	35
H2	60	–	30	35	60	35
H3	30	30	–	45	30	45
H4	35	35	45	–	35	60
H5	60	60	30	35	–	35
H6	35	35	45	60	35	–

Panel 1: Cluster A includes Hospitals 1, 2, and 5

	H1	H2	H3	H4	H5	H6
H1	–	60	30	35	60	35
H2	60	–	30	35	60	35
H3	30	30	–	45	30	45
H4	35	35	45	–	35	60
H5	60	60	30	35	–	35
H6	35	35	45	60	35	–

Panel 2: Cluster B includes 4 and 6. Hospital 3 is added to Cluster B based on relative closeness

providers require time to correct those events and patients require additional time to recover from these complications (Edwards et al. 1991). From an operations standpoint, we argue that adverse events can be thought of as quality defects that cause problems. Thus, poor quality should generally increase ALOS; therefore, lower ALOS indicates better quality. This proposition is supported by an increasing volume of work demonstrating that, across a wide variety of clinical conditions, poor quality care was representative of longer ALOS (Edwards et al. 1991, Thomas et al. 1997). ALOS is also favored by some researchers because it is objective whereas some other quality metrics are self-reported subjective measures.

4.3. Independent and Control Variables

The independent variables—*number of interoperable health information technologies*, *sequence of interoperable health information technologies*, and *distance between sequences*—form the focus of the study and are used to empirically test our hypotheses. Number of interoperable HITs (SEQLENGTH) is a count of the number of integrated technologies (including the CIS if it is present). Technically, any subset of these technologies can be integrated together in any order. However, our *a priori* expectation was that certain technologies would be needed—in a specific order—for the cardiology department to gain the most value from the integrated technologies. To determine which sequence clusters yield better performance, we use a randomly generated split-sample approach.

4.3.1. Split-Sample Approach.

To generate the split sample, we drew a random sample of hospitals of approximately 50% from our full dataset, yielding one "calibration set" consisting of 160 hospitals and a "hold-out set" of 154 hospitals (50.5/49.5% split). Next we created clusters of hospitals based on the method described in Table 1. Using only the calibration set, we identified top performing sequence clusters. For a cluster to be considered a top performer, the average performance of the hospitals within the cluster had to be in the top 30% across all hospitals on all four indicators. The hospitals that were part of a top performing cluster were coded as "1" and all that were not top performers as "0." There were 39 hospitals belonging to six sequence clusters in the top performer category in the calibration set (see Table 2, column 3).

After identifying the top performing clusters, we sent a list containing these six sequence clusters to the hospital CIOs referenced earlier and asked them why these six clusters of cardiology technologies were best performers. The consensus was that those sequences that began with the CIS were the most likely to allow for interoperability and easier integration of subsequent medical technologies. They

also noted that CT scanning was more versatile and easy to integrate than the other medical technologies. An underlying attribute of all except one of the best performing sequences was the presence of the CIS and in four of the six, the CIS precedes all other technologies in the integration process. Further, in four of the sequences, CT was second in sequence. We coded each of these best performing sequence clusters as interoperable sequences (INTEROPSEQ) based on our empirical findings and our experts' justification for these findings.

Using the coding for INTEROPSEQ clusters from the calibration set, we next coded the associated clusters from the "hold-out sample" accordingly and used that sample to test our hypothesis that the similarity of a sequence to an interoperable sequence would influence performance. To assess similarity to an INTEROPSEQ, we computed metrics that capture the distance of any given sequence from the *closest* interoperable sequence (SEQDIST). Specifically, we used the representative sequence from each of the six INTEROPSEQs and calculated the pairwise distance from a focal hospital to each of the six. We then subtracted this similarity score (as discussed in Table 1) from a perfect match score of 60 to yield six unique distance scores corresponding to the closeness of the focal hospital to each INTEROPSEQ. The minimum distance score of the six was used as the focal hospital's SEQDIST value.

4.3.2. Control Variables.

Similar to other industries, standard characteristics influence firm performance.

Table 2 Top Performer Sequence Clusters and Quantity of Hospitals

Cluster	Sequence (order of integration)	Number of hospitals		
		Calibration	Hold-out	Full set
Top 30% performance				
A	CIS-CT-NC-IVUS-EC-CCL	7	9	16
B	CIS-CT-IVUS-CCL-EC-X	17	19	36
C	CIS-EC-CCL-CT-NC-IVUS	4	4	8
D	CIS-CCL-EC-IVUS-NC-CT	1	1	2
E	IVUS-CT-EC-CCL-NC-X	8	9	17
F	EC-CT-IVUS-CIS-CCL-NC	2	3	5
Subtotals		39	45	84
55 clusters	Any sequence with four or more integrations not in top 30% performance	85	102	187
None	Remaining hospitals with two or three integrations*	NA	NA	284*
Totals		124	147	555

*These were not used in the analysis for sequence comparison.

CCL, cardiology catheterization laboratory; CIS, cardiology information system; CT, computed tomography scanning; EC, echocardiology; IVUS, intravascular ultrasound; NC, nuclear cardiology X, did not integrate.

The control variables used in this study include hospital characteristics such as location, size, and age (Devaraj and Kohli 2000, Shi 1996). Each hospital is assessed a location variable based on its zip code (URBAN, LARGE RURAL, SMALL RURAL, or ISOLATED[2]). The size of the hospital is operationalized as the number of staffed beds (STAFFED BEDS), which is used in favor of the total number of beds because many hospitals have non-utilized beds. The age of the hospital is measured in years, and it is also a standard control variable used to account for differences in performance due to infrastructural and other variations that might be attributed to the age of the hospital.

Finally, new technology adoption often improves performance, not just because of the impact from the new technology, but also because of newly improved processes surrounding functions or tasks (Lee and Ozer 2007) and integration with complementary systems (Sambamurthy et al. 2003). An extensive body of literature in organizational learning (Levitt and March 1988) suggests that the amount of experience with a technology affects such factors as productivity and efficiency. Literature also suggests that "lag effects" of technology investments should be an important consideration in examining payoff from technology investments (e.g., Brynjolfsson and Hitt 1996, Kohli and Devaraj 2003). Because of these aspects, we control for the amount of time the hospitals have had the technology (MATURITY). From the HA database, we tracked the time since the integration of each cardiology technology for a given hospital and averaged them to calculate MATURITY for that hospital.

5. Results

Descriptive statistics and correlations between variables for the hold-out sample are presented in Appendix B. The first set of analyses included all hospitals that had two or more technologies integrated into a centralized system. Our results from this set of analyses correspond to a test of hypotheses H1a and b relating length of the technology sequence with performance. An ordinary least squares regression of the independent variables against our four separate dependent variables yielded the results presented in Table 3. Model 1a uses non-adjusted process costs as the dependent variable; Model 1b uses CMI-adjusted process costs as the dependent variable. Model 1c uses non-adjusted ALOS as the dependent variable and Model 1d uses CMI-adjusted ALOS as the dependent variable. Consistent with H1a and b, a greater number of integrated technologies (SEQLENGTH) correlates with lower process costs and increased quality. SEQLENGTH is negative and significant for Model 1a ($p < 0.01$) and Model 1b ($p < 0.01$). The negative sign indicates a greater number of integrated technologies correlates with reduced costs. SEQLENGTH is negative and significant as well for ALOS Model 1c ($p < 0.05$) and Model 1d ($p < 0.05$). A lower ALOS indicates increased quality, as explained earlier. Thus, we find strong support for H1a and b.

The next set of analyses address hypothesis H2a and b relating interoperable sequences and cardiology performance. From this point on in the analysis, we removed all hospitals that had integrated fewer than four technologies. Our justification for this decision was twofold. First, there was no sequence, per se, to analyze because many of the hospitals had only integrated two technologies. Second, we identified that short sequences performed more poorly and, as our intent was to compare sequences of similar length, we limited the analysis to sequences of length four to six. We only used hospitals within the hold-out sample to test hypotheses related to INTEROPSEQ. We

Table 3   Results for Performance Impacts of Sequence Length

Independent and control variables	Dependent variables			
	Model 1a	Model 1b	Model 1c	Model 1d
	Average cost	CMI-adjusted average cost	ALOS	CMI-adjusted ALOS
SEQLENGTH	− 0.132**	− 0.151**	− 0.111*	− 0.073*
Urban	− 0.015	− 0.106	0.290	0.338+
Small rural	− 0.154	− 0.157	− 0.072	− 0.096
Large rural	− 0.189	− 0.272	0.175	0.214
Staffed beds	0.173**	0.164**	0.336**	0.325**
Age	0.043	0.032	0.071	0.084+
R^2	12.4	11.0	24.1	26.2

**$p < 0.01$, *$p < 0.05$, +$p < 0.10$; two-tailed significance test.
ALOS, average length of stay; CMI, case mix index.

established which sequences were INTEROPSEQ using the calibration set and kept the hold-out separate so as not to contaminate any additional analysis. This reduced our sample size to 45 "top 30% performer" hospitals in six clusters and 102 lower performing hospitals in 55 clusters, for a full data sample set of 147 hospitals in 61 clusters.

We conducted two procedures to examine the relationship between sequences and performance. First, we estimated a MANOVA model with the categorical variable INTEROPSEQ as the independent variable and the various performance metrics as the dependent variables. Next, we estimated models with INTEROPSEQ as well as the standard control variables as independent variables. In both situations, our hypotheses are directional and our test is simply whether INTEROPSEQ performs better than the other sequences. Thus, we test the alternative hypothesis H_A: $\mu_{\text{interopseq}} > \mu_{\text{other}}$. The results in Table 4 provide preliminary evidence that hospitals with interoperable sequences performed better on all four metrics: they had lower costs as well as lower ALOS and these differences are all statistically significant.

We test hypotheses H2 and H3 with models 2a–d and estimated separate OLS regression models for each performance dimension with the independent variables INTEROPSEQ, SEQDIST, MATURITY, and control variables. In the first row of Table 5, we observe that INTEROPSEQ relates significantly to performance after controlling for other factors. Models 2a–d illustrate the correlation between membership in the clusters representing INTEROPSEQ with decreased costs (Model 2a, $p < 0.05$; Model 2b, $p < 0.05$) and increased quality (Model 2c, $p < 0.05$; Model 2d, $p < 0.05$), lending further support to H2 beyond the MANOVA results.

Table 4 MANOVA Results for Performance of Interoperable Sequences

Variable	Description	Mean	SD	p-value
Average cost	Interoperable sequences	5961.1	1383.5	0.042**
	Other sequences	6441.6	1456.9	
CMI-adjusted average cost	Interoperable sequences	6149.5	1281.7	0.063*
	Other sequences	6570.6	1464.7	
ALOS	Interoperable sequences	3.835	0.594	0.080*
	Other sequences	3.999	0.592	
CMI-adjusted ALOS	Interoperable sequences	3.723	0.703	0.054*
	Other sequences	3.923	0.607	

**$p < 0.01$, *$p < 0.05$; one-tailed directional t-test.
ALOS, average length of stay; CMI, case mix index.

Our third hypothesis proposed that even if a hospital follows an adoption sequence that is similar to, but not precisely the same as the interoperable cluster, the hospital will experience better cost and quality performance. In all of the models, the significant positive coefficients on the distance variable (SEQDIST, $p < 0.05$) suggest that smaller distance from an INTEROPSEQ yields lower length of stay and lower costs. These results support H3a and H3b.

We find it intriguing that the maturity of the sequences (i.e., those that have been integrated for a longer period of time) had no impact on process costs or quality. We present a more detailed discussion of this finding in the next section. Finally, the number of staffed beds proved to be non-significant for every model except 2d. With CMI-adjusted ALOS as the dependent variable, size was marginally significant, with larger hospitals, unexpectedly, correlating with higher costs and lower quality. Our models account for 9.4–27.5% of variance in our dependent variables.

Table 5 OLS Results for Performance Impacts of Sequence Characteristics

	Dependent variables			
	Model 2a	Model 2b	Model 2c	Model 2d
Independent and control variables	Average cost	CMI-adjusted average cost	ALOS	CMI-adjusted ALOS
INTEROPSEQ	− 0.148*	− 0.183**	− 0.177*	− 0.140*
SEQDIST	0.155*	0.138*	0.171*	0.185*
MATURITY	0.046	0.047	− 0.050	− 0.024
Staffed beds	0.112	0.068	0.104	0.206+
Urban	− 0.078	0.042	− 0.078	0.052
Large rural	− 0.130	− 0.137+	− 0.234	− 0.104
Small rural	− 0.152+	− 0.127	− 0.323+	− 0.274
Age	0.032	0.028	− 0.072	0.025
R^2	11.2	9.4	25.3	27.5

**$p < 0.01$, *$p < 0.05$, +$p < 0.10$; one-tailed directional t-test.
ALOS, average length of stay; CMI, case mix index.

It should also be noted that there was not a consistent increase in Rsq values between Tables 3 and 5 even though we included INTEROPSEQ and SEQDIST as independent variables in the second analysis. Finally, our quality models explained approximately double the variance that our cost models explained.

6. Discussion and Contributions

The results of our analyses point to evidence supporting all three hypotheses proposed in this study. First, we found that the number of cardiology technologies integrated has a positive effect on process costs and process quality. To the extent that the technologies interface with each other, it is reasonable to assume that accurate information in one system will translate and transmit into the other and will equate to richer and more complete data. This conclusion must be tempered within bounds. Our sample had a maximum of six separate technologies to integrate; if there were significantly more, we may see diminishing returns as a result of information overload and bounded rationality. However, for our bounded sample, we see that more information within the IS provides better system performance.

Second, we demonstrate the use of sequencing methods to categorize hospitals based on the order of technologies integrated. We find evidence that interoperable sequences—those which implement foundational IS earlier—outperform other sequences on process costs and process quality. We should note that while the *p*-values are approaching typical threshold values of significance, we believe this may be due in part to the reduced sample of hospitals in the latter analyses after we split the sample. Because we eliminated the short sequence hospitals that tended to perform more poorly, our findings are actually more conservative than they would have been had we retained them.

With respect to the sequences themselves, those with CIS first tended to perform the best and this is likely due to the interoperable nature of the CIS. This core of information in the CIS eliminates duplicate data entry and, coupled with specific results from the other technologies, enables better processes. One example of these benefits is more rapid collection of insurance money for performed services. Our findings support the notion that even if it is more complicated to learn and more expensive, early integration of foundational technologies correlate with improved results. Our interviews with clinicians, CIOs, and a director of cardiology IT suggest that the CIS is not the easiest system to implement, integrate, or learn. In fact, we discovered that the biggest challenge with the integration of the other diagnostic technologies was one of using common image standards. Beyond that aspect, the stand-alone technologies were more similar than different in term of use. Therefore, to inform our work post-analysis, we sent several sequences to our key informants and asked them to classify the technologies based on criteria that they considered important. Their responses suggest that many integration decisions are based on cost/benefit analyses. For example, a CT might be integrated early as a means of cutting down on costly film and/or couriers who transport the film to other departments or hospitals. Further, some of the application technologies, such as a CATH, require video and hemodynamic systems, which make the integration somewhat more complicated. Other classification themes that were provided suggest that the initial cost of the system, the number of users, the complexity of the use of the system, and the desire of the specialized clinicians contribute to the order in which the technologies are integrated.

Finally, we illustrate the sequencing algorithm to estimate the proximity of one sequence to its nearest interoperable sequence. This analysis shows that the proximity to interoperable sequences has a positive impact on outcomes. Thus, the closer a hospital's integration sequence is to an interoperable sequence, the better the hospital will perform. One avenue for future research is a more detailed investigation of the clusters and an examination of what factors contribute to optimal sequence performance.

We did not observe a significant relationship between the maturity of cardiology technologies and performance outcomes. Our discussion with the CIO and medical staff of two local hospitals indicated that most of the cardiology technologies included in our analyses have been around for several years, in some cases more than 10 years. Thus, it might be the case that the cardiology technologies are "mature" technologies, and we do not have variability on this dimension to test this relationship.

The size of the hospital, as measured by the number of staffed beds, proved to be an inconclusive predictor of performance. Some prior research shows that economies of scale in larger hospitals lead to better performance outcomes (Chen et al. 1999). On the other hand, other research shows smaller hospitals can better care for patients and therefore have shorter ALOS and reduced costs (Hedges et al. 1992, Shi 1996). It should be noted, however, that there are several interrelated characteristics of larger hospitals that could have confounding effects on performance. For example, larger hospitals are typically academic/teaching hospitals that tend to draw the most talented physicians but by design also include many inexperienced practitioners in the form of students. Further, because larger hospitals are often located in large cities, procedures are practiced more often, but

they are also more difficult due to the nature of the injuries in cities. It may be true that within a smaller cardiology department it is easier to monitor and control quality and cost aspects. While our results were inconclusive, we would encourage further research into the relationship between hospital size and performance.

Finally, one intriguing finding that warrants further investigation is the amount of variance explained between our quality and cost model. As noted, our quality models explain 10–14% more variance than do the cost models. One explanation for this can be found in our earlier point about measuring performance at the level of the technology implementation. In our study, it seems apparent that our quality measure—ALOS—is something that is a direct result of the process that is taking place within the cardiology department. The cost aspect, while also being examined at the cardio level, is something that is impacted by broader hospital- and industry-level aspects. For example, inefficiencies outside of the cardio department can have some impact on costs, such as group purchasing agreements, outsourcing of image readings, and the allocation of overhead expenses. Even with these limitations, our results are robust and demonstrate a statistical link between our key variables.

6.1. Theoretical Contributions
The most important contribution of this paper is the finding that sequencing, as a methodology for exploring firm performance, is viable and important. This adds to the business value of technology literature and also highlights the importance of investigating the process by which organizations integrate and manage technologies. Some note the gradual and evolving development of information infrastructure and its socio-technical nature (Hanseth and Lyytinen 2004). While we do not disagree that the current processes are gradual and more trial-and-error than best practice, our study suggests that the resulting sequence is associated with hospital performance. Examining order of integration allows us to view the evolution of a process as opposed to a single snapshot in time and lends insight to the process of integration instead of exclusively focusing on the outcome of integration. To our knowledge, no studies have explored whether the order in which technologies are implemented—which is a learning process—will result in performance impacts.

6.2. Managerial Implications
In recent years, strategy scholars have called for new forms of competition in healthcare as a means of driving efficiency and quality improvements (Porter and Teisberg 2004). These calls have not gone unan-

swered as accreditation commissions, such as Joint Commission on the Accreditation of Healthcare Organizations, and large insurance providers, such as the Centers for Medicare and Medicaid Services, have launched mandatory and voluntary programs (e.g., HospitalCompare), which report several standardized quality indicators for US hospitals. The intent of these programs is to make data available to consumers in hopes that they use the information to seek the best care. This transparency has important implications for management and our results provide useful insights. For example, the closer a hospital adheres to one of the defined interoperable integration paths, the better the process outcomes. The integration of cardio technologies is under the control of management and we have identified specific sequences that result in better performance, thus we believe this is an actionable finding. One can derive several second order gains from this finding as well. The most obvious of these is an increased throughput. For hospitals operating at near maximum capacity, this increases the likelihood that a patient will be able to get a bed at that hospital and have their procedure performed. For hospitals operating below this threshold, it translates into a reduced toll on the doctors, nurses, and support staff that must care for the patients while they are in the hospital.

There are also second order benefits that may improve IT vendor performance. Producers of integration software can tailor their tools to work more effectively within the given sequences named above. Even in our example with only six technologies, there are 720 possible installation sequences. If software developers know the "best" sequences, presumably this would cut development time for integration and improve the interoperability of the system. Removing uncertainties related to the next integration would reduce software development time and cost.

Following on the idea of reduced uncertainty, top management in the hospital can minimize their focus on integration decisions and direct their attention to other challenges. Our interviews with clinicians and hospital CIOs suggest that there currently is not a best practice for deciding when and if to integrate technologies. For service providers, best practices will continue to emerge and evolve related to integration sequences. Thus, these providers will be well positioned to suggest the optimal sequence of integration for their customers. While our model is associative and causality should not be inferred, it potentially could provide insights into characteristics of hospitals and their environment that would suggest an optimal integration sequence. We do question, however, whether there is an inflection point at which time the integration of more technologies leads to reduced performance from information overload.

7. Conclusion and Extensions

This study took a fine-grained approach to the relationship between the integration of technologies into centralized IS and performance. While the method we used is novel, our intent was not to showcase this tool, but instead to use it to more deeply investigate a simple research question, that being—"Does sequence matter?" Our results unambiguously suggest that, indeed, sequence does matter. This finding is important because hospitals, like every other firm, need to show the value derived from technology investments. Our study has empirically shown that improvement in cardio costs and cardio quality result when hospitals integrate technologies into an IS in a specific order. While this is an important finding, we cannot say with certainty that these results are generalizable to other departments within hospitals. We also have not investigated the frequency with which procedures are performed using each technology, which may factor into the decision for when to integrate. We would suggest that researchers consider additional performance measures, especially patient satisfaction and health outcomes. Further, a more detailed understanding of why certain sequences work and others do not is warranted. Through our work, we encourage other researchers to look beyond the mere adoption of technologies and dig deeper into the process and management of technologies.

Acknowledgments

Notes

[1] A PACS is a computer and/or network that is used to store, retrieve, distribute, and present medical images including data associated with the image and patient.

[2] These four classifications were established by the University of Washington Rural Health Research Center under a project known as the Rural Urban Commuting Area. The codes are determined based on a formula that takes into account population and transportation infrastructure.

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Appendix A

Confirmation of Medical Technology VS. HIT

The sequences of implementation were based on data provided by HA. As noted in section 4, it is imperative to our study that we are able to identify if and when a medical technology is transformed into an IT. Upon discussion with HA researchers, we found that their research associates call each hospital within their database and ask, "Are you automated for a Cardiology Information System? If so, what vendor is installed?" This defines whether or not the hospital has an integrated foundational IS that encompasses the benefits of PACS but also adds decision support, alerts, and possibly order entry.

They follow up with the following questions, "Are you automated for a Cardiology PACS system? If so, when did you automate each of the following PACS modalities? Cath Lab, CT (Computerized Tomography), Echocardiology, Intravascular Ultrasound, Nuclear Cardiology?"

If the respondent requires further clarification, the research associate notes that "automated is defined as any or all of the modalities that are integrated into the PACS such that images and some documentation are stored in a central repository for access by others."

Appendix B

Table B1 Correlation Table and Descriptive Statistics

Variable description	Mean	SD	1	2	3	4	5	6	7	8	9	10	11
1. Cardiology: average cost (US$)	6338.40	1576.69	1										
2. Cardiology: CMI-adjusted average cost (US$)	6545.47	1576.50	0.979**	1									
3. Cardiology: average length of stay	4.016	0.691	0.598**	0.563**	1								
4. Cardiology: CMI-adjusted average length of stay	3.896	0.747	0.601**	0.517**	0.967**	1							
5. Interoperable sequence	0.244	0.431	−0.090	−0.115	−0.211*	−0.153	1						
6. Sequence distance	11.703	7.252	0.110	0.099	0.105	0.109	−0.143	1					
7. Age	37.61	34.797	0.056	0.038	0.094	0.106	0.115	−0.102	1				
8. Urban	0.780	0.415	0.186*	0.148	0.293**	0.324**	−0.110	0.035	−0.060	1			
9. Large rural	0.134	0.342	−0.157	−0.151	−0.214*	−0.210*	0.110	−0.084	0.077	−0.742**	1		
10. Small rural	0.073	0.261	−0.088	−0.038	−0.227**	−0.272**	0.004	0.105	−0.010	−0.530**	−0.111	1	
11. Number of staffed beds	336.24	214.873	0.323**	0.283**	0.383**	0.417**	−0.132	0.104	0.124	0.279**	−0.324**	0.088**	1
12. Maturity	3.769	1.942	0.069	0.059	−0.008	0.006	−0.087	0.200*	0.033	−0.016	−0.029	0.061	0.141**

$**p < 0.01$, $*p < 0.05$; two-tailed significance test.
CMI, case mix index.