

# Technology Integration in Service Supply Chains: An Empirical Analysis of Electronic Medical Record Integration by Healthcare Providers

## Abstract

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An array of information-intensive and customer-centric technologies is available today that promise significant performance improvements for manufacturing and service supply chains. Managers are overwhelmed by the abundance of such technologies. And, increasingly, managers are finding it challenging to determine what each of the available technologies do, which technologies they should invest in, and how to integrate the technologies so that the promised performance benefits of the technologies can be realized. The extant supply chain management and information system literatures provide limited insights into strategies for technology integration and its implications for performance, especially in the context of *service supply chains*. This paper, based on the first part of my dissertation research, is an attempt to address this gap in the literature.

The context of my dissertation research is service supply chain operations. Specifically, we investigate technology selection and technology integration in the context of healthcare supply chains. We conceptualize technology integration in the healthcare supply chain by way of a classification scheme for clinical information technologies (electronic medical records) comprising of five levels. The levels are ordered with respect to an increasing order of medical record preparedness – i.e., information storage and access capability to coordinate and support superior quality and timely clinical decision making. Drawing on the relevant streams of academic and practitioner literatures, we posit the following proposition that guides the empirical analysis: Healthcare providers that select a higher level of technology integration will outperform the healthcare providers that select a lower level of technology integration. The performance measure we investigate is patient turnover measured as patient-discharges per bed.

By way of research design, we model a healthcare provider's choice of a level of technology integration as a discrete choice model. Given the limitation of traditional regression approaches in accounting for self-selection in decision making, this study adopts an econometric technique corrected for self-selection to examine the level of technology integration selection process and its impact on operational performance. The research design involves the use of a two-step selection model to account for the endogeneity bias. Electronic medical records (EMR), that entail the capture, storage, retrieval and transmission of patient-specific healthcare-related data and whose successful operation is dependent on the tight integration of various clinical information technologies across the healthcare supply chain, is the technological domain of our research. Based on data from 1011 acute care providers in the US, our results suggest that healthcare providers self-select into different levels of technology integration in the context of their supply chains. While some healthcare providers are better off investing in higher levels of technology integration and benefit from doing so, others are better off not following suit.

**Keywords:** Service Supply Chain, Healthcare Supply Chain, Technology Integration, Self-Selection, Econometric Analysis, Electronic Medical Records (EMR).

## **1. Introduction**

Technological development in the recent years has significantly impacted supply chain operations. An array of information-intensive and customer centric information technologies (IT) available today for manufacturing and service supply chains alike, promise enormous benefits such as improved quality, increased flexibility, and reduced costs, from enhanced coordination and integration (Moody 2006, Kearns and Lederer 2003). However, managers are often overwhelmed by the abundance of these technologies in the marketplace, as they find it hard to figure out what each of these technologies do, which ones they should purchase, and how to successfully integrate them in their organization's existing routines and enhance performance (McAfee 2006). Further, a recent survey of senior executives found that 10% of managers felt that they were getting high returns from IT investments whereas 47% informed that returns were low, negative or unknown (CSC & FERF 2005). Such findings make a manager cautious while investing in the customer-centric technologies and inhibit partners in service supply chains to realize the full potential of these technologies.

Extant research in the academic literature on technology and performance parallels this observation. Results of empirical studies that investigated the relationship between information technologies and performance are mixed. While some studies have shown no effect or even negative impact (Loveman 1994, Strassman 1990) others highlight a positive impact (e.g. Menon et al. 2000, Dewan & Min 1997, Kelley 1994). The mixed results in the empirical research studying impact of technology on performance can be attributed to the failure of the estimation models to consider a host of factors that have the potential to affect performance and/or the failure to consider the integration aspects between different technologies (Bharadwaj 2000).

While several contingency factors (e.g., Li & Ye 1999, Powell & Dent-Micallef 1997, Mata et al. 1995) are identified in understanding the performance effects of technology

investments, the inappropriate choice of technologies and the lack of integration across the selected technologies (i.e. the contingency among technologies themselves) is the most under-investigated (Orlikowski & Iacono 2001, Colombo & Mosconi 1995). A meta-analysis of models across disciplines proposed to explain the relationship between technology and performance found that the contingency among technologies was not included in any one of those models (Heine et al. 2003). While extant research has been focused on the complex issues associated with systems design, development, and implementation, there is little research on integration of technology applications (Waring & Wainwright 2000), particularly as it relates to service supply chains. This study is a step towards filling this gap in the literature.

The empirical context of this study is service supply chain operations. Specifically, it is focused on the technology selection and technology integration issues in healthcare supply chains. The healthcare service is where we find more variability and uncertainty at the point of service than in any other economic activity (Li & Benton 2006). Investments in IT in the healthcare industry grew by more than three times from \$6.5 billion in 1990 to \$23.6 billion in 2003 (Carpenter 2004). Given the growing significance of technologies in healthcare supply chains and the potential of technologies in improving healthcare delivery, it is crucial for researchers to focus attention on the adoption, integration, and implementation issues in this context. This research serves to address this need and is guided by the following questions:

- ❖ How do healthcare providers select a level of technology integration?
- ❖ What are the performance implications of providers, given their choice of the level of technology integration?

In this research, we conceptualize different levels of technology integration based on the presence or absence of different clinical information technologies adopted by a healthcare

provider. We adopt a capability perspective to identify the different levels of technology integration. The higher the level of technology integration, more the number of technologies, with additional technologies in each level building on capabilities from technologies in lower levels leading to a superior capability,. Healthcare providers that have the highest level of technology integration are posited to be the most advanced in terms of capabilities with the highest level of medical record preparedness by way of information storage and access to information that facilitates superior quality and timely clinical decision-making. Building on the conceptual foundation, we then empirically assess the performance implications of technology integration levels. Given the presence of significant selection effects in the firm's choice of technology integration levels, the research design involves the use of a two-step selection model to account for the endogeneity bias. The empirical analysis is based on data from 1011 acute care providers in the US. The results of the analysis suggest that while healthcare providers with higher levels of technology integration realize better operational performance on average, conditional on observed and unobserved factors, healthcare providers self-select themselves into different technology integration levels. In other words, while some healthcare providers are better suited to investing in higher levels of technology integration and benefit from doing so, not all providers choose to follow suit. The implications of the study findings, conclusions, and directions for future research are identified.

The remainder of the paper is organized as follows. Section 2 provides the theoretical background for the study. It provides a brief discussion on the extant research on technology integration and performance and develops the central research hypothesis. Section 3 provides an overview of self-selection and develops the statistical models to account for self-selection. Section 4 provides the research design of the study – the independent variables and data

collection. Next it presents a discussion of the study results. Section 5 presents the conclusions of the study.

## **2. Theoretical Background**

### **2.1 Technology Integration in the Healthcare Supply Chain – Electronic Medical Records (EMR)**

*Technology integration* in a supply chain is the choice of various technologies with different functionalities to deliver a unique application that provides a new service, process, or product. Technology integration has always been challenging (Mantz et al. 1983) but the proliferation of technologies and technology vendors have made it more important and relevant than ever before (Iansiti & West 1997). Technological ‘push’ in the form of enormous increases in computing power and software sophistication achieved in the last few decades have enabled integration of the various islands of automated information processing and decision support systems to form broader systems (De Meyer & Ferdows 1985). These integrated systems have gained acceptance as necessary components of successful, competitive business, despite their high costs, and in some cases, risk (Kumar & Hillegersberg 2000). The various information systems when integrated creates an environment that provides a degree of interoperability which standalone, componentized systems failed to achieve. The integrated system not only enable process automation, but also provides the ability to disseminate timely and accurate information which results in improved managerial and employee decision-making (Hitt et al. 2002). Next, we provide a brief description of technology integration in healthcare supply chains.

In healthcare supply chains, the inability to share information represents one of the major impediments to progress toward shared care and cost containment (Grimson et al. 2000). It was not until the 1990s that healthcare supply chains attempted to integrate different clinical information systems (Borzekowski 2002), which leverages the power of technologies such as

clinical decision support systems for physicians (Ball et al. 2003). Electronic Medical Record (EMR) systems, that forms the context of this research entails the capture, storage, retrieval, transmission, and coordination of patient-specific healthcare-related data, including clinical, administrative, and biographical details (Brailer & Terasawa 2003, Raghupathi 1997). Successful operation of EMR systems is dependent on the tight integration of the clinical information technologies that allows a greater degree of process automation of routine tasks as well as more comprehensive data analysis and reporting capabilities to improve physician and management decisions. EMR systems are posited to have the potential to improve operational efficiency and patient safety while also increasing health and other social benefits to the health care industry (Hillstead et al. 2005).

The need for computerized patient records caught everyone's attention when the Institute of Medicine (IOM 1991) published a report calling for the elimination of paper-based patient records within ten years, but the progress has been slow and this goal has not been met (Overhage et al. 2002). Though there are some noteworthy examples of healthcare settings which have successfully deployed EMR systems (Overhage 2003, Kolodner & Douglas 1997), they are mostly the exception. A recent IOM report (2002) observed that "in most of the nation's hospitals, orders for medications, laboratory tests, and other services are still written on paper and many hospitals lack even the capability to deliver laboratory and other results in an automated fashion." Though many healthcare providers have adopted EMR systems, there is certainly huge variation in their respective systems. We say that this heterogeneity is caused by the availability and/or lack of the clinical information technologies, which are the constituents of an integrated EMR system and there is a need of classifying EMR systems into levels of technology integration.

Given the lack of a validated classification system in extant literature, in this study we identify attributes of a set of technologies that tend to have similar impact on performance and group them together. Our grouping of technologies is informed by Garets & Davis's (2006) *clinical transformation staging model* that is intended to evaluate the implementation of EMR systems in healthcare supply chains.

We develop a classification system for the technology integration based on the availability of nine clinical information technologies (see table 1) that corresponds to different levels of EMR systems. Following the studies of IOM (2002) and Garets & Davis (2006), we group the nine clinical technologies into four groups with each group providing the healthcare provider a set of information storage and access capabilities. Based on the four groups, we develop five *levels of technology integration*. Healthcare providers that do not have any one of the three technologies in group 1 belong to *Level One* of technology integration, and providers that have all the nine clinical technologies belong to the highest level i.e. *Level Five* of technology integration. Healthcare providers representing higher levels of technology integration are equipped with a higher number of technologies which, in turn, provide the healthcare providers with superior information storage and access capabilities.

-----Insert Table 1 about here-----

## **2.2 Technology Integration and Performance**

Studies that have investigated impact of technology on performance focused mostly on a specific technology (Hill & Scudder 2002, Mukhopadhyay et al. 1995). While this approach may be necessary, it is not sufficient because it misses the opportunity of understanding the relationship between multiple technologies. Researchers studying relationship between multiple technologies and performance in manufacturing supply chains have often considered the number of technologies as the measure of technological capability (Dunne & Schultz 1995, Doms et al.

1994), ignoring the performance impacts of specific technology combinations. One exception is the Beede & Young (1998) paper that studied the relationships between specific technologies and technological combinations and the various measures of operational performance in an effort to investigate the impact of advanced manufacturing technologies on operational performance. Based on a study of 7000 US manufacturing plants, they found that plants with integrated operations that adopted a complex technology combination (involving seven or more technologies) generally had higher labor productivity and production worker earning levels as compared to plants that failed to do so. Ward & Zhou (2006) found internal IT integration aimed at generating information and facilitating information sharing, has a positive influence on customer lead time when mediated with lean and JIT practices.

Review of the extant literature shows that the impact of information systems on performance has been investigated from different theoretical perspectives such as transaction cost economics theory (Subramani 2004, Amit & Zott 2001), information processing model (Cooper & Wolfe 2005), and the resource-based view (Bharadwaj 2000, Mata et al. 1995). In this study we attempt to advance this literature by investigating the performance impact of the level of technology integration in healthcare supply chains.

Huber (1990) while studying the effects of advanced information technologies posited that use of computer assisted decision support and communication technologies enables increased information accessibility leading to higher quality decisions and reduction in time required to make such decisions. These improvements in quality and timeliness of “organizational intelligence and decision making” directly increase the efficiency with which goods and services are produced. Melville et al. (2004) suggested that any one of the technology applications can be sourced as a package or service but when all of these heterogeneous

applications are selected and adapted to business processes of the focal organization in a supply chain, then the ultimate result is often valuable. Technology integration, which refers to integration of multiple technology applications each with unique functionalities, thus provides economic value. For our research, we extend Huber's (1990) proposed theory by introducing technology integration and argue that integration of multiple advanced information technologies will significantly reduce the time necessary to make decisions and also guide managers and technology users to take higher quality decisions. And improvements in decision making will translate in superior operational performance.

Healthcare supply chains are particularly information intensive supply chains where the need for information sharing and coordination is very high. Hence, healthcare supply chains are likely to benefit from improved information processing and sharing capabilities enabled by the availability and integration of the different clinical information technologies. When clinical information technologies (like decision support systems) enable sharing of information with storage technologies (like medical imaging) and ancillary technologies (like radiology or pharmacy), not only repetitive and routine processes in a healthcare supply chain are automated but also physician judgment and decision-making are enhanced. As we discussed earlier, such timely and higher quality decision-making will result in faster execution and delivery of patient-care and positively impact operational performance. In essence, greater technology integration enables healthcare providers to perform better. Hence, we posit the following proposition:

**Proposition:** Ceteris paribus, operational performance for healthcare providers who select a higher level of technology integration will be superior to healthcare providers who select a lower level of technology integration.

### 3. Self Selection

In the last section, we suggested that healthcare providers, typically, choose from one of five levels of technology integration and that providers at a higher level of technology integration perform better than providers at a lower level of technology integration. However, adoption of a level of technology integration involves the investment of a considerable amount of organizational resources (e.g., costs of technology, infrastructure, employee training, and other relevant management initiatives). This makes the decision making job of the technology managers challenging since investments in technology is associated with the need to provide economic justification (Devaraj & Kohli 2003). Extant literature suggests that managers make choices to generate sustainable competitive advantage and superior performance outcomes. In other words, managers do not make strategic decisions randomly, but based on expectations of how their choices will affect future performance (Hamilton & Nickerson 2003). For example, when faced with the *make* versus *buy* decision, managers who choose to *make* may have particular production capabilities that make it a highly profitable choice, while managers who lack the production capabilities may instead choose to *buy*.

We believe that given the nontrivial allocation of resources demanded by the higher levels of technology integration, managers choose technologies and the integration level based on their expectations of performance benefits from such investments. We posit that managers self-select themselves into different levels of technology integration based on the extent to which they believe choosing a particular level of technology integration is aligned with their overall operations strategy. In the selection of the appropriate level of technology integration, managers weigh the expected benefits of choosing a level of technology integration against the costs of investments in these technologies. The operations management literature is replete with studies (e.g. Skinner 1974) that advocate the adoption of a focused approach to managing operations,

particularly manufacturing operations, that is aligned with business strategy. In the same vein, we argue that different managers will adopt different levels of technology integration that is consistent with their business strategy.

Identifying the performance benefits of the different levels of technology integration forms one of the key objectives in this research. However, if managers self-select themselves into different levels of technology integration that is optimal given their attributes and that of their industry, an empirical model that does not account for self-selection would be misspecified, and the empirical estimates and the normative conclusions drawn from the analysis can be misleading (Shaver 1998, Masten 1993). When managers make a strategic decision in their choice of level of technology integration, a comparison of performance of healthcare providers that have chosen one level of technology integration to those that have chosen another level is not feasible given that healthcare providers are not chosen randomly assigned to these “treatments” (Rubin 1974). From a methodological perspective, the failure to explicitly take into account the nonrandom sorting of the choice of a managerial decision, in the *buy* versus *make* example or in the choice of the level of technology integration in our research, leads to endogeneity bias – the statistical bias that arises when an endogenous variable is treated as exogenous (Heckman 1974). The bias associated with endogeneity arises due to the existence of unobserved heterogeneity, which refers to differences across observations affecting both the selection and performance “*that are nonrandom but also not subject to direct measurement.*” This unobserved heterogeneity can lead to contemporaneous correlation between that explanatory variable and the error term, resulting in biased coefficient estimates. To estimate unbiased coefficient estimates in such situations we require econometric methods that statistically account for manager’s self-selection into a particular level of technology integration

(Masten 1996). A traditional regression analysis with performance as dependent variable and the levels of technology integration would be inappropriate unless it is assumed either that managers randomly select different levels of technology integration or that all factors affecting performance can be measured and included in the model (Shaver 1998). However, these conditions hardly ever hold true in actual settings.

Consequently, in this research, we adopt an econometric self-selection model introduced by Heckman (1979) and Lee (1978) that takes into account the self-selection in estimating the effect of choosing different levels of technology integration on operational performance. The self-selection procedure involves two key steps: In the *first* step, the choice of a particular level of technology integration by the healthcare provider is modeled. And in the *second* step, the normative effect of the choice of the level of technology integration on performance of the healthcare provider is assessed. Further, in this research we conduct additional analyses to assess the costs of failing to choose the normatively correct decision. This involves the use of counterfactual analysis where alternative *what-if* scenarios are empirically evaluated to serve as decision-tools for healthcare providers in their choice of the level of technology integration. We provide a brief overview of the self-selection model and the counterfactual analysis below:

### **3.1 Model Formulation**

**Step One: Level of Technology Integration Selection** – This step models the technology integration level choice of the healthcare provider. The five levels of technology integration discussed earlier, form the five discrete choices. We use an ordered probit model (since a manager has five choices where the choices are ordered) to predict the level of technology integration which each healthcare organization has selected. The level choice is modeled as a continuous latent variable  $L_i^*$ , which is given by:

$$L_i^* = \delta \mathbf{Z}_i + \beta \mathbf{X}_i + v_i, \quad (1)$$

where  $\delta$  and  $\beta$  are the vector of parameters to be estimated,  $\mathbf{Z}_i$  represents factors that affect level choice but that do not affect performance,  $\mathbf{X}_i$  represents all characteristics that affect the choice of the technology integration level and performance, and  $v_i$  represents the unobserved factors influencing the level choice. The estimates  $\delta$  and  $\beta$  in (1) are computed using ordered probit regression model. The provider's technology integration level choice is based on its  $L_i^*$  value relative to four cut-off points -  $cut_1$ ,  $cut_2$ ,  $cut_3$ , and  $cut_4$ , which are maximum likelihood estimates (Maddala 1983, Idson & Feaster 1990) from the selection equation (1). For example, providers select  $L_2$  if  $cut_1 < L_i^* < cut_2$ .

**Step Two: Normative Effects** – In this step, we assess the performance benefits of the selection of level of technology integration by providers, accounting for the selection process. The performance outcome for each level of technology integration  $\Pi_{ij}$  is given by:

$$\Pi_{ij} = \beta_j \mathbf{X}_i + \varepsilon_{ij} \quad (j=1, 2, 3, 4 \text{ and } 5). \quad (2)$$

This equation can be estimated by ordinary least squares (OLS) using the sub-samples of organizations choosing that particular level choice. However, as discussed earlier, the equation above can be estimated only when all the factors affecting performance and choice of technology integration level are observable and included in the regressions. If there are unobserved factors affecting the choice of the technology integration level and performance, then  $[E(\varepsilon_{ji} | j) \neq 0]$ , which leads to biased estimates of  $\beta_j$  (Hamilton & Nickerson 2003).

Accounting for the non-zero covariances arising out of unobserved factors in the selection and performance equations above, performance for healthcare providers that choose each level of technology integration can be re-specified as:

$$\Pi_{1i} = \beta_1 \mathbf{X}_i - \sigma_1 * (\phi [cut_1 - \mathbf{X}_i \beta + \mathbf{Z}_i \delta]) / \Phi [cut_1 - \mathbf{X}_i \beta + \mathbf{Z}_i \delta] + \varepsilon_{1i} \quad (3)$$

$$\Pi_{2i} = \beta_2 \mathbf{X}_i + \sigma_2 * (\phi [cut_1 - \mathbf{X}_i \beta + \mathbf{Z}_i \delta] - \phi [cut_2 - \mathbf{X}_i \beta + \mathbf{Z}_i \delta]) / (\Phi [cut_2 - \mathbf{X}_i \beta + \mathbf{Z}_i \delta] - \Phi [cut_1 - \mathbf{X}_i \beta + \mathbf{Z}_i \delta]) + \varepsilon_{2i} \quad (4)$$

$$\Pi_{3i} = \beta_3 \mathbf{X}_i + \sigma_3 * (\phi[\text{cut}_2 - \mathbf{X}_i \beta + \mathbf{Z}_i \delta] - \phi[\text{cut}_3 - \mathbf{X}_i \beta + \mathbf{Z}_i \delta]) / (\Phi[\text{cut}_3 - \mathbf{X}_i \beta + \mathbf{Z}_i \delta] - \Phi[\text{cut}_2 - \mathbf{X}_i \beta + \mathbf{Z}_i \delta]) + \varepsilon_{3i} \quad (5)$$

$$\Pi_{4i} = \beta_4 \mathbf{X}_i + \sigma_4 * (\phi[\text{cut}_3 - \mathbf{X}_i \beta + \mathbf{Z}_i \delta] - \phi[\text{cut}_4 - \mathbf{X}_i \beta + \mathbf{Z}_i \delta]) / (\Phi[\text{cut}_4 - \mathbf{X}_i \beta + \mathbf{Z}_i \delta] - \Phi[\text{cut}_3 - \mathbf{X}_i \beta + \mathbf{Z}_i \delta]) + \varepsilon_{4i} \quad (6)$$

$$\Pi_{5i} = \beta_5 \mathbf{X}_i + \sigma_5 * (\phi[\text{cut}_4 - \mathbf{X}_i \beta + \mathbf{Z}_i \delta]) / (1 - \Phi[\text{cut}_4 - \mathbf{X}_i \beta + \mathbf{Z}_i \delta]) + \varepsilon_{5i} \quad (7)$$

For each equation (3) through (7), the error terms in the performance equations capture the performance effects of variables that are not identified or measured in the specified  $\mathbf{X}_i$ . Here we assume that the error terms from equations (1) and (2),  $v_i$ , and the  $\varepsilon_{ji}$ 's are jointly normally distributed so that expressions for  $E(\varepsilon_{1i} | L_1)$ ,  $E(\varepsilon_{2i} | L_2)$ ,  $E(\varepsilon_{3i} | L_3)$ ,  $E(\varepsilon_{4i} | L_4)$  and  $E(\varepsilon_{5i} | L_5)$  are tractable. The expected values for each error term are now zero due to inclusion of the second component in each equation which is referred to in the literature as the inverse Mills ratio and can be mathematically expressed as  $\lambda = \phi[\cdot] / \Phi[\cdot]$  where  $\phi[\cdot]$  is the normal density and  $\Phi[\cdot]$  is the cumulative normal distribution. The terms  $\sigma_1$  through  $\sigma_5$  are the coefficients of the inverse Mills ratio terms in the performance equation for providers opting for each level of technology integration respectively.  $\sigma_1 \neq 0$  or  $\sigma_2 \neq 0$  or  $\sigma_3 \neq 0$  or  $\sigma_4 \neq 0$  or  $\sigma_5 \neq 0$  indicates the presence of endogeneity. When  $\sigma_1 = \sigma_2 = \sigma_3 = \sigma_4 = \sigma_5 = 0$ , the level choice is exogenous. The OLS estimation of equations (3) through (7) will give us the unbiased estimates of  $\beta_1$ ,  $\beta_2$ ,  $\beta_2$ ,  $\beta_4$ ,  $\beta_5$ ,  $\sigma_1$ ,  $\sigma_2$ ,  $\sigma_3$ ,  $\sigma_4$ , and  $\sigma_5$ .

### **Counterfactual Analysis: Costs of Mistakes**

Thus far, we have assessed healthcare provider's selection of levels of technology integration and subsequent performance implications. Next we focus on the question: What if the healthcare provider had chosen any other level of technology integration? How would their performance change under the counterfactual scenario? In other words, in this step we address these costs of making mistakes i.e. failing to choose the normatively correct decision (Masten et al. 1991, Masten 1993). In our research, healthcare providers choose from five ordered levels of technology integration. Hence, in this step we conduct counterfactual analyses for consequently

ordered pairs of technology integration levels (i.e., *levels I & II*, *levels II & III*, *levels III & IV*, and *levels IV & V*). We describe the model for the first pair (*levels I & II*) below:

Consider a provider that has chosen *level I* of technology integration. Its performance under this chosen strategy is obtained from equation (3). This performance can be contrasted with its expected performance had it chosen *level II* of technology integration. To calculate the expected performance under the (counterfactual) other choice, we multiply its vector of attributes  $\mathbf{X}_i$ , with the corresponding coefficients from the performance equation for the *level II* of technology integration. This is given as:

$$E[\Pi_{i1} | \Pi_{2i} > \Pi_{1i}] = \beta_2 \mathbf{X}_i - \sigma_2 * (\Phi[\text{cut}_1 - \mathbf{X}_i \beta + \mathbf{Z}_i \delta]) / \Phi[\text{cut}_1 - \mathbf{X}_i \beta + \mathbf{Z}_i \delta] + \varepsilon_{1i} \quad (8)$$

Now consider an organization that has chosen *level II* of technology integration. Its performance under this chosen strategy is obtained from equation (4). This performance can be contrasted with its expected performance had it chosen *level I* of technology integration. Following the reasoning applied above, we compute the expected performance under the counterfactual scenario as:

$$E[\Pi_{i1} | \Pi_{2i} > \Pi_{1i}] = \beta_1 \mathbf{X}_i + \sigma_1 * (\Phi[\text{cut}_1 - \mathbf{X}_i \beta + \mathbf{Z}_i \delta] - \Phi[\text{cut}_2 - \mathbf{X}_i \beta + \mathbf{Z}_i \delta]) / (\Phi[\text{cut}_2 - \mathbf{X}_i \beta + \mathbf{Z}_i \delta] - \Phi[\text{cut}_1 - \mathbf{X}_i \beta + \mathbf{Z}_i \delta]) \quad (9)$$

## 4. Research Design

### 4.1 Variables and Model Specification

As discussed earlier, we model the selection process for each level of technology integration as a discrete choice model (an ordered probit model) that is driven by variables indicative of manager's choice of different technologies. While it is desirable to include all the factors affecting the level of technology integration selection process, it is often not possible to observe or measure all the variables. Consequently, in the Probit specification we include variables that we have information on and the error term is set to include the effects of the unobserved and unmeasured factors. Specifically, in this study, we model the healthcare

provider's technology selection process as a function of the following variables: *Busoff*, *Finance*, *Humres*, *Decision*, *Mgcare*, *Medrec*, *Clinical*, *ProfitStatus*, *FormalSteer*, *PurSubY*, *ServiceType*, *Licensebed*, *Ftype1*, *VPAMember*, *PGMember*, *CIOtoCEO*, *KeyExecMem*, and *MemNonKey*.

According to complementarity theory, organizations selecting a set of complementary technologies will perform better than those without the possible set of complementary technologies (Fennel 1984, Colombo & Mosconi 1995). A healthcare provider, an information-intensive unit, employs a large number of various administrative and strategic decision support systems apart from the clinical technologies. These information systems though not specifically related to patient-care, serve to address the administrative functions (e.g., billing, personnel), strategic decision support applications, strategic planning, resource allocation, etc., (Austin & Bowerman 2003). These technologies have an important role to play in the healthcare provider's objective to provide quality service and can be considered as complementary technologies with the clinical technologies considered for the different levels of technology integration. Hence, in the selection of technologies considered in the levels of technology integration, managers will be influenced by the availability of the other information systems such as *Busoff*, *Finance*, *Humres*, *Decision*, *Mgcare*, *Medrec* and *Clinical* (See table 1).

We include the number of licensed beds (*LicenseBed*) at the acute care facility - a commonly used measure of organizational size, as a key control variable in our study, since size has been found to play a significant role in the adoption of total quality management programs, administrative innovations, MRI technology (Friedman & Goes 2000, Westphal et al. 1997, Kimberly & Evanisko 1981), advanced manufacturing technologies and flexible manufacturing systems (Ettlie et al. 1984), integrated service digital networks, open systems technology, and electronic data interchange (Chau & Tam 2000, Premkumar et al. 1997).

In the healthcare supply chain, the information requirements for the production and coordination of care and consequently the technology requirements increase with the provision of highly specialized services, the delivery of higher acute care, and care provision along a continuum (Burke 2002). Consequently, we control for the *type of service* (four types of services, general medical and surgery - *stype1*, academic - *stype2*, long term acute – *stype3*, and others comprising of critical access, pediatric and orthopedic care providers – *stype4*).

We account for the *ProfitStatus* of healthcare providers – a dichotomous variable which captures the type of governance (for-profit or not-for-profit), considered to be an important predictor affecting performance (Shukla et al. 1997) and selection of various constituent technologies for the different levels of technology integration.

Steering Committees are high-level teams of representatives from multiple stakeholders of healthcare supply chains who are entrusted with the task of linking IT strategy with business strategy by setting a strategic direction (Nolan 1982). Steering committees not only communicate the benefits and implications of IT investments to top management and user groups, but also play a major role in strategic IT planning (Drury 1984), the quality of Information Systems planning (Gupta & Ragunathan 1989, Doll & Torkzadeh 1987), and its effectiveness (Premkumar & King 1992, Ein-Dor & Segev 1978). Following these research findings, we control for the presence of formal steering committees and the membership structure of such committees (*FormalSteer*, *KeyExecMem* & *MemNonKey*) to account for their influence on the managerial decision making in the selection of technologies.

Support from top management (chief executive officers and physicians) is found to be significant in the successful adoption of medical records imaging (Friedman & Goes 2000). Chief Information Officer (CIO) reporting directly to the Chief Executive Officer (CEO), a

practice by “leading edge” adopters of IT (Smaltz et al. 2006), sends a visible signal to other decision makers of the value of IT, aligns IT considerations with the business model of the healthcare provider, and places the CIO in a position of considerable power, a predictor of innovation adoption in organizations (Baldrige & Burnham 1975). Also, healthcare providers differ in terms of the availability of a purchasing sub-committee, which decides on issues relating to technology procurement. The presence of such sub-committees clearly indicates the top-management willingness and focus on information technology sophistication of the provider. Consequently, in our model for the selection of technologies in healthcare providers, we account for the CIO’s Reporting Status (*CIOtoCEO*) and the presence of a purchasing sub-committee (*PurSubY*).

The Integrated Delivery Systems (IDS), one of the major trends that swept the health care industry over the last fifteen years, significantly increased investment in IT (Burns et al. 2001). Being a part of the IDS, the healthcare providers benefit in terms of network learning since all the member organizations in a healthcare supply chain share their experience from technology selection to implementation stages (McCullough 2005). Higher the *membership of an IDS* (i.e., higher the number of healthcare providers belonging to the IDS, denoted by *Ftype1*), greater is the network learning, affecting choice of level of technology integration. Hence, we include it in our selection model.

Communication within and across organizations arising from exposure to professional societies, and conference attendance, plays a pivotal role in selection of technologies, particularly in healthcare (Tabak & Jain 2000, Bobrowski & Bretschneider 1994). Healthcare providers participate in strategic hospital alliances (SHA) which increases the number of communication channels available to the participating members. In our selection model, we

consider two variables, *member of purchasing group* and *member of purchasing alliance*, to account for the influence of communication channels in a healthcare provider's selection of the level of technology integration.

For the performance equation in second step of our analysis as discussed earlier, the dependent variable is *discharges per licensed bed*, and the independent variables in the specification include: *ServiceType*, *Clinical*, *Medrec ProfitStatus*, *Usage*, *total networking applications*, *total outsourced services*, *presence of wireless and Intranet*, *Ftype1*, *membership of IDS*, and the inverse Mills ratio terms. The independent variables in the specification capture the influence of different organizational characteristics on the performance (*discharges per licensed bed*) for a healthcare provider.

*Discharge per Licensed Beds* is defined as the total discharges divided by the number of beds in service at the healthcare provider. It measures the number of patients who use a provider's beds during a given period. Since it indicates the relationship between inputs (beds) and outputs (discharges), discharges per bed is a measure of productivity and has been used in healthcare research to measure patient turnover (Shortell et al. 2005).

The information systems payoff literature has largely overlooked the effect of technology usage on performance (Devaraj & Kohli 2003). Organizational benefits from strategic investments in clinical technologies and specific patient-care applications considered in the different levels of technology integration (technology) (task) in our research are moderated by the technology usage. Consequently, we consider *usage* of technologies, as one of the determinants of performance. We define usage as a ratio: (# of technologies in use)/ (# of technologies in use + # of technologies not in use)

Technology integration is enabled not only by the different clinical information technologies considered for the different levels of technology integration but also with the availability of other networking technologies and integration equipments, availability of Intranet, and finally, the availability of wireless technologies. When we are investigating the impact of the levels of technology integration on operational performance, we believe that the presence/absence of such technologies will certainly make a difference and, hence, consider the following variables – namely, *total networking applications* and the *presence of Intranet and wireless* – in our estimation model to determine operational performance.

#### **4.2 Data Collection**

Our research is designed to address how healthcare providers select different levels of technology integration and then understand the impact of their selected level of technology integration on operational performance. The unit of analysis is the healthcare provider and the sampling frame consists of United States acute care providers. The data for this study combines two databases - Dorenfest Complete IHDS+ Database and Cost Reports Database. The Dorenfest Complete IHDS+ Database serves as the foundation of this research. It contains detailed information about the healthcare systems of nearly 30,000 healthcare providers associated with 1,444 integrated health care delivery systems for the year 2003. Dorenfest and Associates collect detailed information on technological and demographic characteristics of healthcare organizations using mailed surveys and telephone interviews every year (since 1990). Chief Information Officers (CIOs) report the specifics about information technology and the Vice Presidents of Marketing and/or Strategic Planning are interviewed for demographic data. The database contains detailed data on more than 50 healthcare information system applications, purchase plans for all information technology activities, information system decision-making process, and steering committee composition for each healthcare provider. Also, it contains

demographic data of all healthcare providers by type (e.g. acute, sub-acute, ambulatory, home health), sizing statistics (e.g. bed size, full time equivalents, etc.), contact information for 19 key executives for each healthcare provider and overall information technology strategy. The Medicare Cost Reports database from the Healthcare Cost Report Information Systems (HCRIS), which is the only national database that uses standard definition and carries information on performance variables (annual financial and operational characteristics for the universe of acute care providers), formed our source for data on the operating performance.

To construct the research sample, we focused on the Dorenfest database of 4005 acute care providers. For each healthcare information system used in this research, we checked whether a healthcare provider has that type of technology and developed a table with the healthcare provider's identifier and the existence (or non-existence) of each information system. Then we used our definition of levels of technology integration to focus on the nine clinical information technologies to form the five levels. Overall, this information was gathered for 1011 acute care providers. Information on independent variables used in the research was collected for each healthcare provider. In the next step, the data was linked with the Cost Reports dataset using Medicare Identification Numbers. Approximately 80% of available healthcare providers from the Dorenfest database could be matched successfully with the cost reports information. The Cost Reports enabled us to compute a large number of financial and operating performance measures for acute care providers (Sourcebook 2003) included in our data.

### **4.3 Results and Discussion**

In this section, we provide a discussion of the results from the empirical analysis corrected for self-selection. Table 2 provides descriptive statistics of the key variables in the study. Columns 2 to 6 provide the values for key variables (in Column 1) for healthcare providers belonging to the five levels of technology integration identified in our study. We

observe that variables *Decision* and *Clinical* technologies are more pronounced for healthcare providers with higher technology integration levels, although the other technologies *Busoff*, *Finance*, *Humres* are quite similar. Also, we do not find much variation in the variables *ProfitStatus*, *FormalSteer* and *Usage* across the levels of technology integration.

-----Insert Table 2 about here-----

Table 3 provides estimates of the ordered probit model representing the selection process for the five levels of technology integration of the research variables discussed in section 3. Here we observe that there are many variables that affect the selection of the technology integration levels in healthcare providers. These variables reflect the technological (*Busoff*, *Decision*, *Medrec*, *Clinical*), structural (*CIOtoCEO*, *MemNonKey*) and other characteristics (*Licensebed*, *ProfitStatus*, *Ftype1*, *VPAMember*) of the provider. The performance analysis in the next step shed further light on this issue.

-----Insert Table 3 about here-----

Table 4 reports the results from separate regressions for the five levels of technology integration. The regression models (Columns 2-6) for each of the five integration levels account for the selectivity bias through the inclusion of inverse mills ratios calculated from the ordered probit selection equation reported on Table 3. We observe that the coefficients for the inverse mills ratios for columns 2 through 4 are statistically significant, suggesting that providers self-select themselves into the different technology integration levels. The significant selection effects indicate the existence of unobservables common to both the selection process and performance (i.e. *discharges per bed* in our research), which if not explicitly treated as endogenous, would bias our estimates of the relationship between levels of technology integration and operational performance. Since the error of the reduced-form probit selection is

truly a composite of the managerial choice and performance equations it is difficult to economically interpret the signs of the inverse mills ratios (Idson and Feaster 1990). We can infer from the results in Table 4 that there is self-selection – i.e., managers chose a level of technology integration based on factors which they believe will provide their organization the best possible operational performance, although not all these factors are observable by the researcher.

-----Insert Table 4 about here-----

In the next step, we conduct analysis focused on understanding the performance implications of different levels of technology integration considered two at a time. Specifically, we follow the two-step selection model discussed in section 3, for healthcare providers that have chosen the two levels of technology integration in focus. We ran a probit selection equation and estimated the inverse mills ratios from the probit model. In the second step, we ran two OLS regression for each level of technology integration with the independent variables that influences operational performance and the inverse mills ratios, the dependent variable being *discharges per bed*. We also describe results from the counterfactual analyses described earlier.

Table 5A reports the results from separate OLS regressions for the two levels of technology integration – level I and level II. The OLS regression models for the performance equation are corrected for selectivity bias with the inclusion of inverse mills ratios calculated from the probit selection equation. We observe that the coefficient for the inverse mills ratios for level 1 is positive and statistically significant. The positive coefficient indicates a positive selection by the 176 healthcare providers into level I of technology integration. This suggests that the average performance for 176 healthcare providers who have selected level I of technology integration will be higher than the average performance of all the 363 (= 176 + 187)

providers if all of them were randomly assigned to level I of technology integration. On the other hand, the coefficient for the inverse mills ratios for level II is not statistically significant. This means that healthcare providers who have selected level II of technology integration have no unobservable advantage or disadvantage above and beyond the average performance. Table 5B provides the mean counterfactual estimates. The diagonal elements in the table correspond to the predicted performance for the observed choices and the off-diagonals correspond to the predicted values under the counterfactual (alternative) option. The counterfactual estimates suggest that if the healthcare providers that chose level I of technology integration had instead chosen level II (move from quadrant II to quadrant III), their performance by way of discharges per bed would have increased significantly from 27.7 to 41.5 ( $p < 0.01$ ). Similarly, if healthcare providers that chose level II of technology integration had instead chosen level I (move from quadrant IV to quadrant I), then their performance would have significantly dropped from 43.83 to 18.49 ( $p < 0.01$ ). This suggests that while performance increases from level I to level II, some healthcare providers choose to adopt level I owing to unobservable factors affecting the selection process.

-----Insert Tables 5A and 5B about here-----

Table 6A reports the results from separate OLS regressions for the two levels of technology integration – level II and level III, corrected for selection bias. We observe that the coefficient for the inverse mills ratios for level II is positive and statistically significant. The positive coefficient indicates a positive selection by the 187 healthcare providers into level II of technology integration. This suggests that the average performance for 187 healthcare providers who have selected level II of technology integration will be higher than the average performance of all the 684 (= 187 + 497) healthcare providers if all of them were randomly assigned to level II of technology integration. The coefficient for the inverse mills ratios for level III is not

statistically significant. This suggests that healthcare providers in level III of technology integration have no unobservable advantage or disadvantage over the average performance. Results from the counterfactual analysis (see table 6B), suggest no statistically significant difference in the performances between the observed choices and the counterfactual options. This suggests that while there is no performance difference between levels II and III, some healthcare providers choose to adopt level II owing to unobserved factors affecting the selection process.

-----Insert Tables 6A and 6B about here-----

Table 7A reports the results from separate OLS regressions for the two levels of technology integration – level III and level IV, corrected for selection bias. We observe that the coefficient for the inverse mills ratios for level III is positive and statistically significant. The positive coefficient indicates a positive selection by the 497 healthcare providers into level III of technology integration. This suggests that the average performance for 497 healthcare providers that have selected level III of technology integration will be higher than the average performance of all the 621 (= 497 + 124) healthcare providers if all of them were randomly assigned to level III of technology integration. The coefficient for the inverse mills ratios for level IV is positive and statistically significant. The sign of the coefficient indicates a negative selection, i.e., the performance of the 124 healthcare providers in level IV will be lower than the average performance of all 621 healthcare providers in a random allocation to level IV. While this seems counter-intuitive, a possible explanation for the negative selection is that providers invest in higher level technologies with the intention to grow with the payoffs from the investment realized over a long-term. The counterfactual estimates (see table 7B) suggest that if the healthcare providers that chose level III of technology integration had instead chosen level IV

(move from quadrant II to quadrant III), their performance by way of discharges per bed would have increased significantly from 42.7 to 58.6 ( $p < 0.01$ ). Similarly, if healthcare providers that chose level IV of technology integration had instead chosen level III (move from quadrant IV to quadrant I), then their performance would have significantly dropped from 50.6 to 31.58 ( $p < 0.01$ ). This reinforces the finding earlier that while performance may be higher for healthcare providers choosing level IV, some healthcare providers choose level III owing to unobserved factors affecting the selection process. The results from two-step analyses for technology integration levels – level IV and level V, revealed no significant endogeneity bias. Consequently, we do not report the results of further analyses here.

-----Insert Tables 7A and 7B about here-----

The pattern of results above suggests that operational performance improves with higher levels of technology integration. This provides conditional support for our proposition where we posit that performance for healthcare providers that select higher level of technology integration will be greater than healthcare providers that select lower level of technology integration. However, we also find that healthcare providers choose into lower levels of technology integration owing to unobserved factors that affect the selection process. Also, we find that performance of healthcare providers who have self-selected into different levels is greater than the average performance under a random allocation into those levels. For example, 27.7 (quadrant II) is higher than 18.49 (quadrant I) in table 6A and 42.7 (quadrant II) is higher than 31.58 (quadrant I) in table 6C. This signifies the importance of self-selection and informs us that managers have chosen specific levels of technology integration based on their evaluations of characteristics of extant operations and expectations of how their choices affect future performance.

## 5. Conclusions

Despite the growing significance of technologies in the healthcare supply chains, little systematic understanding exists on the integration of technologies, the selection or performance implications of technology integration. Managers are keen on learning what technologies to invest in, how to select the appropriate level of integration, and what performance implications may be expected of the technology selection and integration. This study makes an effort towards addressing these issues. It makes a three-fold contribution in this area.

*First*, we conceptualize technology integration by way of a classification scheme of levels of technology integration comprising of various clinical technological applications employed in healthcare supply chains. While focused on healthcare supply chains, the proposed conceptualization may be extended, more generally, to services supply chains. *Second*, we account for self-selection of organizations into different levels of technology integration. In our research, we show that there is systematic self-selection into technology integration levels: while the conventional wisdom is that higher levels of technology integration translate into superior performance, we find that managers choose the level of technology integration based on observable and unobservable factors. *Third*, we demonstrate the link between levels of technology integration and operational performance based on an econometric analysis of data from approximately 1011 healthcare providers. From the standpoint of managerial practice, the paper sheds light into how technology integration affects operational performance and highlights the role of selection into technology integration levels. Also, this study which investigates technology integration in healthcare supply chains can provide new explanations on the inconsistencies in the extant literature of the actual benefits of IT investments, referred to as the ‘productivity paradox.’

There are several possible research extensions to this study that could prove useful. *First*, future research could focus on the performance differentials within the same level of technology integration. This would shed light on the reasons why healthcare providers selecting the same level of technology integration perform differently. *Second*, future research could focus on the role of supply chain readiness in the effective implementation of technologies by healthcare providers. Specifically, research could look into the role of three key participants - administration, physicians, and support staff, - the moderating effects of the supply chain technology infrastructure. Third, from this study we found that there are unobservable factors that influence managerial decisions to select advanced information technologies. We can extend this research and empirically investigate the unobservable factors to understand the process of information technology selection by managers. Finally, this is a cross-sectional study. Hence, another interesting topic of future inquiry can be the study of the phenomenon of technology integration over time and investigate how performance is affected with the changes in the levels of technology integration over time.

## References

- Amit, R. & Zott, C. 2001. Value Creation in E-Business. *Strategic Management Journal*, 22(6): 493-520
- Austin, C. J. & Bowerman, S. B. 2003. *Information Systems for Healthcare Management*, 6<sup>th</sup> edition, Chicago: Health Administration Press
- Baldrige, J. & Burnham, R. 1975. Organizational Innovation: Individual, Organizational and Environmental Aspects. *Administrative Science Quarterly*, 20: 165-176
- Ball, M. J., Weaver, C. & Abbott, P. A. 2003. Enabling Technologies Promise to Revitalize the Role of Nursing in an Era of Patient Safety. *International Journal of Medical Informatics*, 69: 29-38
- Beede, D. N. & Young, K. H. 1998. Patterns of Advanced technology Adoption and Manufacturing Performance. *Business Economics*, 33: 43-48
- Bharadwaj, A. S. 2000. A Resource-Based Perspective on Information Technology Capability and Firm Performance: An Empirical Investigation. *MIS Quarterly*, 24(1): 169- 193
- Borzekowski, R. 2002. Measuring the Cost Impact of Hospital Information Systems: 1987-1994. *Finance and Economics Discussion Series*, 42, Board of Governors of the Federal Reserve System, Washington
- Brailer, D. J., & Terasawa, E. L. 2003. Use and Adoption of Computer-based Patient Records in the United States: A Review and Update. *California Healthcare Foundation*. March 28. Oakland, CA.
- Burke, D. E. 2002. *Information Technology Strategy - Environmental Fit and Hospital Financial Performance*, Doctoral Dissertation, March 2002, Auburn University
- Burns, L. W., Walston, S. L., Alexander, J. A., Zuckerman, H. S., Andersen, R. M., Torrens, P. R. & Hilberman, D. 2001. Just How Integrated are Integrated Delivery Systems? Results from a National Survey. *Health Care Management Review*, 26(1): 20-39
- Carpenter, D. 2004. Capital and IT. *Hospitals & Health Networks*, 78(5): 7-9
- Chau, P. Y. K. & Tam, K. Y. 2000. Organizational Adoption of Open Systems: A technology-push, need-pull Perspective. *Information & Management*, 37(5): 229-239
- Colombo, M. G. & Mosconi, R. 1995. Complementarily and Cumulative Learning Effects in the Early Diffusion of Multiple Technologies. *Journal of Industrial Economics*, 43(1): 13-48
- Cooper, R. B. & Wolfe, R. A. 2005. Information Processing Model of Information Technology Adaptation: An Intra-Organizational Diffusion Perspective. *The DATA BASE for Advances in Information Systems*, 36(1): 30-48
- Corbett, M. F. 2002. VHA/Corbett Study Shows Hospital Outsourcing Spending Increased 15 Percent in past year. *Business Wire*, Sept. 7, 613-613
- CSC & FERF 2005. The Seventh Annual Survey of Technology Issues for the Financial Executives. *CSC World*, July/September 2005
- Davenport, T. H. 1998. Putting the Enterprise into the Enterprise System. *Harvard Business Review*, 76(4): 121-131

- De Meyer, A. & Ferdows, K. 1985. Integration of Information Systems in Manufacturing. *International Journal of Operations & Production Management*, 5(2): 5-12
- Devaraj, S. & Kohli, R. 2003. Performance Impacts of Information Technology: Is Actual Usage the Missing Link?. *Management Science*, 49(3): 273-289
- Dewan, S. & Min, C.K. 1997. The Substitution of Information Technology for Other Factors of Production: A Firm Level Analysis. *Management Science*, 43(12): 1660-1675
- Doll, W. J. & Torkzadeh, G. 1987. The Relationship of MIS Steering Committees to Size of Firm and Formalization of MIS Planning. *Communications of the ACM*, 30(11): 972-978
- Drury, D.H. 1984. An Evaluation of Data Processing Steering Committees. *MIS Quarterly*, 8(4): 257-265
- Ein-Dor, P. & Segev, E. 1978. Organizational Context and the Success of Management Information Systems. *Management Science*, 24(10): 1064-1077
- Ettlie, J. E., Bridges, W. & O'Keefe, R. 1984 Organizational Strategy and Structural Differences for Radical versus Incremental Innovation. *Management Science*, 30(6): 682-695
- Fennell, M. L. 1984. Synergy, Influence and Information in the Adoption of Administrative Innovations. *Academy of Management Journal*, 27(1): 113-129
- Friedman, L. H. & Goes, J. B. 2000. The Timing of Medical Technology Acquisition: Strategic Decision Making in Turbulent Environments. *Journal of Healthcare Management*, 45(5): 317-330
- Galbraith, J. 1973. *Designing Complex Organizations*, Reading, MA: Addison-Wesley
- Garets, D. & Davis, M. 2006. Electronic Medical records v. Electronic Health records: Yes, there is a Difference. *HIMSS Analytics White Paper*, Jan2006, 1-14
- Grimson, J., Grimson, W. & Hasselbring, W. 2000. The SI Challenge in Health Care . *Communications of the ACM*, 43(6): 46-55
- Gupta, Y. P. & Ragunathan, T. S. 1989. Impact of Information Systems (IS) Steering Committees on IS Planning. *Decision Sciences*, 20(4): 777-793
- Hamilton, B. H. & Nickerson, J. A. 2003. Correcting for Endogeneity in Strategic Management Research. *Strategic Organization*, 1(1): 51-78
- Heckman, J. 1974. Shadow Prices, Market Wages, and Labor Supply. *Econometrica*, 42: 679-694
- Heckman, J. 1979. Sample Selection Bias as a Specification Error. *Econometrica*, 47: 153-161
- Heine, M. L., Grover, V & Malhotra, M. K. 2003. The Relationship between Technology and Performance: a Meta-Analysis of Technology Models. *Omega*, 31(3): 189-204
- Hill, C. A. & Scudder, G. D. 2002. The Use of Electronic Data Interchange for Supply Chain Coordination in the Food Industry. *Journal of Operations Management*, 20(4): 375-387
- Hillstead, R., Bigelow, J., Bower, A., Giroso, F., Meili, R., Scoville, R. & Taylor, R. 2005. Can Electronic Medical Record Systems Transform Health Care? Potential Health benefits, Savings, and Costs. *Health Affairs*, 24(5): 1103-1117
- Hitt, L. M., Wu, D. J. & Zhou, X. 2002. Investment in Enterprise resource Planning: Business Impact and Productivity Measures. *Journal of Management Information Systems*, 19(1): 71-98

- Huber, G. P. 1990. A Theory of the Effects of Advanced Information technologies on organizational Design, Intelligence, and Decision Making. *Academy of Management Review*, 15(1): 47-71
- Iansiti, M. & West, J. 1997. Technology Integration: Turning Great Research into Great Products. *Harvard Business Review*, 75(3): 69-75
- Idson, T. & Feaster, D. 1990. A Selectivity Model of Employer-Size Wage Differentials. *Journal of Labor Economics*, 8: 99-122
- Institute of Medicine 1991. *The Computer-Based Patient Record: An Essential Technology for Health Care*, eds. R. S. Dick and E. B. Steen, Washington, D.C.: National Academy Press
- Institute of Medicine 2002. *Key Capabilities of an Electronic Health Record System*, Letter Report, Washington, D.C: National Academies Press
- Kearns, G. S. & Lederer, A. L. 2003. A Resource-Based View of Strategic IT Alignment: How Knowledge Sharing creates Competitive Advantage. *Decision Sciences*, 34(1): 1-29
- Kelley, M. 1994. Productivity and Information Technology: The Elusive Connection. *Management Science*, 40(4): 1406-1425
- Kimberly, J. & Evanisko, M. 1981. Organizational Innovation: The Influence of Individual, Organizational, and Contextual Factors on Hospital Adoption of Technological and Administrative Innovations. *Academy of Management Journal*, 24(4): 689-713
- Kolodner, R. M. & Douglas, J. V. 1997. *Computerizing Large Integrated Health Networks: The VA Success*. Springer Verlag
- Kumar, K. & Van Hillegersberg, J. 2000. ERP Experiences and Evolution. *Communications of the ACM*, 43(4): 22-24
- Lee, L. F. 1978. Unionism and Wage Rates: A Simultaneous Equation Model with Qualitative and Limited (censored) Dependent Variables. *International Economic Review*, 19: 415-433
- Li, L. & Benton, W. C. 2006. Hospital Technology and Nurse Staffing Management Decisions. *Journal of Operations Management*, 24: 676-691
- Li, M. & Ye, L. R. 1999. Information technology and Firm Performance: Linking with Environmental, Strategic and Managerial Contexts. *Information and Management*, 35(1): 43-51
- Loveman, W. 1994. An Assessment of the Productivity Impact of the Information Technologies. In T. J. Allen and M. S. Scott Morton (Eds.) *Information Technology and the Corporation of the 1990s: Research Studies*, Cambridge, MA: MIT Press
- Maddala, G. S. 1983. *Limited-Dependent and Quantitative Variables in Econometrics*, Cambridge: Cambridge University Press,
- Masten, S. E. 1993. Transaction Costs, Mistakes, and Performance: Assessing the Importance of Governance. *Managerial and Decision Economics*, 14: 119-129
- Masten, S. E. 1996. Empirical Research and Transaction Cost Economics: Challenges, progress, Directions. in J. Grownwegen (ed.) *Transaction Cost Economics and Beyond*, 43-64, Boston, MA: Kluwer

- Mata, F. J., Fuerst, W. L. & Barney, J. B. 1995. Information Technology and Sustained Competitive Advantage: A Resource-Based Analysis. *MIS Quarterly*, 19(4): 487-505
- McAfee, A. 2006. Mastering the Three Worlds of Information Technology. *Harvard Business Review*, 84(11): 141-149
- McCullough, J. S. 2005. *The Adoption and Diffusion of Hospital Information Systems*, Doctoral Dissertation, University of Pennsylvania
- Melville, N., Kraemer, K. & Gurbaxani, V. 2004. Information Technology and Organizational Performance: An Integrative Model of IT Business Value. *MIS Quarterly*, 28(2): 283-322
- Menon, N. M., Lee, B. & Eldenburg, L. 2000. Productivity of Information Systems in the Healthcare Industry. *Information Systems Research*, 11(1): 83-92
- Moody, P. E. 2006. With Supply Management, Technology Rules! *Supply Chain Management Review*, 10(4): 41-48
- Moustakis, V. 2000. Materials Requirement Planning – MRP. Technical Report, Management Systems Lab, Department of Production and Management Engineering, technical University of Crete, Jan2000
- Mukhopadhyay, T., Kekre, S. & Kalathur, S. 1995. Business Value of Information Technology: A Study of Electronic Data Interchange. *MIS Quarterly*, 19(2): 136-156
- Nolan, R. L. 1982. Managing Information Systems by Committee. *Harvard Business Review*, 40: 72-79
- Orlikowski, W. J. & Iacono, S. C. 2001. Research Commentary: Desperately Seeking the IT in IT Research – A Call to Theorizing the IT Artifact. *Information Systems Research*, 12(2): 121-134
- Overhage, J. M., Middleton, B., Miller, R. A., Zielstorff, R. D. and Hersh, W. R. 2002. Does National Regulatory Mandate of Provider Order Entry Portend Greater benefit Than Risk for Health Care Delivery? The 2001 ACMI Debate. *J AM Med Inform Assoc*, 9(3): 199-208
- Overhage, J. M. 2003. Enhancing Public Health, Health Care System, and Clinician Preparedness: Strategies to promote Coordination and Communication- The Indiana Network for Patient Care (PowerPoint Presentation)
- Powell, T. C. & Dent-Micallef, A. 1997. Information technology as Competitive Advantage: the Role of Human, Business, and Technology Resources. *Strategic Management Journal*, 18(5): 375-405
- Premkumar, G. & King, W. R. 1992. An Empirical Assessment of Information Systems Planning and the Role of Information Systems in Organizations. *Journal of Management Information Systems*, 9(2): 99-125
- Premkumar, G., Ramamurthy, K. & Crum, M. 1997. Determinants of EDI Adoption in the Transportation Industry. *European Journal of Information Systems*, 6(2): 107-121
- Raghupathi, W. 1997. Health Care Information Systems. *Communications of the ACM*, 40(8): 81-82
- Rogers, E. 1995. *Diffusion of Innovations*, 4<sup>th</sup> Edition, The Free Press, New York
- Rubin, D. 1974. Estimating Causal Effects of Treatments in Randomized and Nonrandomized Studies. *Journal of Educational Psychology*, 66: 688-701
- Shaver, J. M. 1998. Accounting for Endogeneity when Assessing Strategy Performance: Does Entry Mode Choice Affect FDI Survival . *Management Science*, 44(4): 571-585

- Shortell, S. M., Schmittiel, J., Wang, M. C., Li, R., Gillies, R. R., Casalino, L. P., Bodenheimer, T. & Rundall, T. G. 2005. An Empirical Assessment of High-Performance Medical Groups: result from a National Study. *Medical care research and Review*, 62(4): 407-434
- Shukla, R. K., Pestian, J. & Clement, J. 1997. A Comparative Analysis of Revenue and Cost-Management Strategies of Not-for-Profit and For-Profit Hospitals. *Hospital Health Service Administration*, 42(1): 117-134
- Skinner, W. 1974. The Focused Factory. *Harvard Business Review*, 52(3): 113-121
- Smaltz, D. H., Sambamurthy, V. & Agarwal, R. 2006. The Antecedents of CIO Role Effectiveness in Organizations: An Empirical Study in the Healthcare Sector. *IEEE Transactions on Engineering Management*, 53(2): 207-222
- Sourcebook 2003. Comparative Performance of U.S. Hospitals The Sourcebook. Solucient Dec 2003
- Strassman, P. A. 1990. *The Business Value of Computers*, Information Economics Press, New Cannan,
- Subramani, M. R. 2004. How Do Suppliers Benefit from Information Technology Use in Supply Chain Relationships. *MIS Quarterly*, 28(1): 45-73
- Ward, P. & Zhou, H. 2006. Impact of Information Technology Integration and Lean/Just-In-Time Practices on Lead-Time Performance. *Decision Sciences*, 37(2): 177-203
- Waring, T. & Wainwright, D. 2000. Interpreting Integration with respect to Information Systems in Organizations – Image, Theory and Reality. *Journal of Information Technology*, 15(1): 131-148
- Westphal, J., Gulati, R. & Shortell, S. M. 1997. Customization or Conformity? An Institutional and Network Perspective on the Content and Consequences of TQM Adoption. *Administrative Science Quarterly*, 42(2): 366-395
- Wholey, D. R., Padman, R., Hamer, R. & Schwartz, S. 2001. Determinants of Information Technology Outsourcing among Health Maintenance Organizations. *Health Care Management Science*, 4(3): 229-239

**Table 1: Levels of Technology Integration**

<u>Capability Group</u>	<u>Constituent Technologies</u>
C1	Laboratory Information Systems, Pharmacy Information Systems and Radiology Information Systems
C2	Clinical Data Repository, Clinical Documentation and Clinical Decision Support Systems
C3	Medical Records Imaging and Picture Archiving Communication Systems
C4	Computerized Physician Order Entry
<u>Levels</u>	<u>Organizational Criteria for Level Membership</u>
1	C1 < 3
1	C1 = 3
3	C1 = 3 and C2 = 3
4	C1 = 3 and C2 = 3 and C3 = 2
5	C1 = 3 and C2 = 3 and C3 = 2 and C4 = 1

Description of Health Information Systems Considered as Independent Variables

<u>Functional Group</u>	<u>Functions</u>	<u>Constituent Technologies</u>
BUSREF	Business Office	Patient Registration, Patient Scheduling, Patient Billing, Electronic Claims, Credit/Collections
FINANCE	Financial Management	General Ledger, Accounts Payable, Materials Management, Enterprise Resource Planning
HUMRES	Human Resource	Payroll, Time & Attendance, Personnel Administration, Benefits Administration
DECISION	Decision Support	Cost Accounting, Flexible Budgeting, Case Mix Analysis, Executive Info Systems, Outcomes & Quality Management
MNCARE	Managed Care	Premium Billing, Eligibility, Contract Management
MEDREC	Medical Records	Master Patient Index, Abstracting, Encoder, Chart Tracking / Locator, Chart Deficiency, Transcription, Dictation
CLINICAL	Medical Records	Pharmacy Dispensing, Surgery, Cardiology, Order Communications/Results, Nurse Staffing, Intensive Care (Critical Care), Computerized Patient Record, Point of Care (Med/Surg Bedside term), Obstetrical Systems, Emergency Department

**Table 2: Descriptive Statistics of the Key variables in the Study**

	Column Two	Column Three	Column Four	Column Five	Column Six
<b>Variable</b>	<b>Level One N=176</b>	<b>Level Two N=187</b>	<b>Level Three N=497</b>	<b>Level Four N=124</b>	<b>Level Five N=27</b>
Business Office (max = 5)	4.11 (0.829)	4.31 (0.632)	4.67 (0.495)	4.82 (0.407)	4.85 (0.456)
Financial Management (max = 4)	2.74 (0.788)	2.96 (0.400)	3.42 (0.519)	3.13 (0.363)	3.19 (0.396)
Human Resources (max = 4)	3.07 (1.224)	3.48 (0.827)	3.92 (0.295)	3.90 (0.394)	3.74 (0.526)
Decision Support (max = 5)	2.06 (1.384)	2.73 (1.28)	4.64 (0.787)	4.54 (0.706)	4.30 (1.265)
Managed Care (max = 3)	0.32 (0.618)	0.69 (0.882)	1.61 (0.912)	1.52 (1.13)	1.37 (1.006)
Medical Records (max = 7)	4.89 (2.01)	6.23 (1.145)	6.82 (0.554)	6.73 (0.59)	6.59 (0.747)
Clinical Applications (max = 9)	1.24 (1.381)	3.23 (1.443)	6.34 (1.813)	7.05 (1.641)	6.48 (1.369)
# of Licensed Beds	87.15 (86.094)	171.82 (119.17)	188.98 (139.418)	328.16 (215.104)	327.93 (212.203)
# of Acute Care managed by IHDS	34.01 (27.333)	34.33 (64.77)	79.51 (74.095)	11.93 (37.644)	13.70 (40.175)
Member of Voluntary Purchasing Alliance (0/1)	0.77 (0.422)	0.81 (0.396)	0.91 (0.288)	0.75 (0.437)	0.78 (0.424)
Member of Purchasing Group (0 or 1)	0.29 (0.457)	0.36 (0.481)	0.23 (0.422)	0.34 (0.477)	0.15 (0.362)
ProfitStatus (0 or 1)	0.22 (0.414)	0.19 (0.392)	0.54 (0.49)	0.06 (0.234)	0.04 (0.192)
FormalSteer (0 or 1)	0.87 (0.333)	0.88 (0.330)	0.88 (0.329)	0.95 (0.217)	0.81 (0.396)
# of Key Executives in IS Steering Committee	3.45 (2.34)	3.40 (1.952)	2.85 (1.744)	3.56 (2.121)	3.19 (1.798)
# of Non-Executives in IS Steering Committee	2.52 (3.846)	1.66 (1.981)	5.25 (6.199)	2.36 (2.709)	1.85 (2.032)
PurSubY (0 or 1)	0.29 (0.456)	0.18 (0.383)	0.43 (0.495)	0.16 (0.3720)	0.22 (0.424)
Usage	0.991 (0.031)	0.998 (0.012)	0.995 (0.018)	0.998 (0.011)	0.989 (0.028)
Total networking technologies	12.17 (5.045)	12.87 (4.903)	13.50 (3.6760)	12.80 (4.157)	13.26 (3.437)
Organization have Wireless	0.19 (0.393)	0.06 (0.246)	0.33 (0.472)	0.20 (0.405)	0.30 (0.465)
Organization have Intranet	0.80 (0.402))	0.79 (0.408)	0.85 (0.355)	0.92 (0.275)	0.89 (0.32)
Discharges per Bed	28.05 (17.486)	43.755 (15.335)	42.782 (18.906)	50.793 (15.669)	48.613 (15.055)

Note – Columns 2-6 report mean values with SDs in parentheses.

**Table 3: Selection Equation for Five Levels of Technology Integration**

Variable	Ordered Probit Selection Equation
Business Office	0.261* (0.091)
Financial Management	0.001 (0.104)
Human Resources	0.067 (0.075)
Decision Support	0.375* (0.050)
Managed Care	0.028 (0.053)
Medical Records	0.123**(0.050)
Clinical Applications	0.406* (0.029)
# of license beds	0.340* (0.056)
ProfitStatus	-0.688* (0.127)
Presence of Formal IS Steering Committee	-0.218 (0.156)
Presence of Purchasing Sub-committee	-0.193 (0.127)
# of Members in IHDS	0.004* (0.001)
Member of Voluntary Purchasing Alliance	-0.287** (0.131)
Member of Purchasing Group	-0.125 (0.100)
CIO reports to CEO	-0.173*** (0.100)
# of Key Executives in IS Steering Committee	0.021 (0.025)
# of Non-Executives in IS Steering Committee	-0.072* (0.018)
n	1011
Wald $\chi^2$ (df)	680.72
Prob > $\chi^2$ (df)	0.0000

**Table 4: Performance Equation Estimates for Five levels of Technology Integration**

Variable	Level One N=176	Level Two N=187	Level Three N=497	Level Four N=124	Level Five N=27
Medical Records	0.049 (0.780)	-0.677 (0.934)	2.72** (1.279)	4.108*** (2.37)	6.682 (5.303)
Clinical Applications	1.238 (1.445)	-0.206 (1.211)	-0.148 (0.832)	-1.694 (1.961)	3.791 (6.209)
ProfitStatus	4.547 (4.786)	0.543 (3.869)	-7.938* (2.851)	-5.797 (5.76)	111.65 (98.397)
Usage	24.773 (28.423)	44.739 (112.38)	67.356 (46.197)	-158.06 (139.39)	10.891 (67.90)
# of Members in IHDS	-0.087*** (0.048)	0.092*** (0.053)	-0.010 (0.026)	-0.102 (0.087)	-0.595 (0.652)
Total Networking technologies	0.323 (0.413)	0.052 (0.350)	0.268 (0.349)	0.094 (0.448)	0.174 (1.679)
Total # of Outsourced IT Services	-0.008 (0.601)	-0.816 (0.683)	0.736*** (0.427)	1.395 (0.968)	0.073 (3.62)
Presence of Wireless	0.510 (3.583)	-2.414 (3.932)	2.746 (2.298)	0.758 (2.999)	-11.27 (7.789)
Presence of Intranet	-0.065 (3.667)	-0.402 (3.159)	-4.307*** (2.608)	-0.828 (5.759)	9.559 (5.494)
<b>Inverse Mills Ratio (<math>\lambda</math>)</b>	-7.619** (3.331)	6.756* (2.112)	4.351*** (2.491)	5.164 (4.399)	-0.292 (11.982)
R square	0.2819	0.1299	0.3660	0.1252	0.5316

Note – Numbers in parentheses are Standard Errors. The performance equations additionally contain controls for the service type. \*Significant at 1%, \*\* Significant at 5% and \*\*\* Significant at 10%

**Table 5A: Performance Equation for Technology Integration Levels – I and II**

Variable	Level One (N=176)	Level Two (N=187)
Medical Records	0.162 (0.761)	-0.119 (0.977)
Clinical Applications	-0.031 (1.718)	2.246 (1.303)
ProfitStatus	7.123 (5.943)	-0.252 (3.985)
Usage	23.046 (28.312)	36.041 (104.538)
# of Members in IHDS	-0.104 (0.055)	0.094 (0.057)
Total Networking technologies	0.319 (0.414)	0.141 (0.358)
Total # of Outsourced IT Services	-0.191 (0.615)	-0.887 (0.705)
Presence of Wireless	0.621 (3.523)	-3.281 (4.585)
Presence of Intranet	0.846 (3.574)	-1.769 (3.268)
<b>Inverse Mills Ratio (<math>\lambda</math>)</b>	12.067* (4.479)	2.439 (5.589)
R square	0.2422	0.0830

Note – Both regression additionally contains a constant and control service type.

\* Significant at 1%, \*\* Significant at 5% and \*\*\* Significant at 10%

**Table 5B: Counterfactual Estimates for Levels of Technology Integration**

	Level One N =176	Level Two N = 187
<b>If Level One</b>	27.7 <i>Quadrant II</i>	18.49 <i>Quadrant I</i>
<b>If Level Two</b>	41.5 <i>Quadrant III</i>	43.83 <i>Quadrant IV</i>

**Table 6A: Performance Equation for Technology Integration Levels – II and III**

Variable	Level Two (N=187)	Level Three (N=497)
Medical Records	0.002 (0.884)	3.303* (1.284)
Clinical Applications	0.728 (1.213)	1.438 (0.701)
ProfitStatus	-1.377 (3.948)	-8.081* (2.909)
Usage	64.839 (109.04)	31.481 (45.549)
# of Members in IHDS	0.098*** (0.054)	-0.025 (0.026)
Total Networking technologies	0.049 (0.342)	0.410 (0.356)
Total # of Outsourced IT Services	-0.821 (0.699)	0.913** (0.406)
Presence of Wireless	-2.868 (4.209)	1.651 (2.208)
Presence of Intranet	-0.034 (3.244)	5.003 (2.641)
<b>Inverse Mills Ratio (<math>\lambda</math>)</b>	9.124** (3.597)	-1.896 (3.036)
R square	0.1116	0.0801

Note – Both regression additionally contains a constant and control service type.

\* Significant at 1%, \*\* Significant at 5% and \*\*\* Significant at 10%

**Table 6B: Counterfactual Estimates for Levels of Technology Integration**

	Level Two (N = 187)	Level Three (N = 497)
<b>If Level Two</b>	43.83 <i>Quadrant II</i>	43.44 <i>Quadrant I</i>
<b>If Level Three</b>	41.7 <i>Quadrant III</i>	42.7 <i>Quadrant IV</i>

**Table 7A: Performance Equation for Technology Integration Levels – III and IV**

Variable	Level Three (N=497)	Level Four (N=124)
Medical Records	2.641** (1.303)	4.123*** (2.27)
Clinical Applications	0.426 (0.529)	-0.683 (1.057)
ProfitStatus	-4.46 (3.279)	0.129 (7.065)
Usage	56.97 (45.506)	-150.223 (146.329)
# of Members in IHDS	0.001 (0.026)	-0.106 (0.092)
Total Networking technologies	0.279 (0.344)	0.052 (0.444)
Total # of Outsourced IT Services	0.649 (0.406)	1.657 (1.027)
Presence of Wireless	2.008 (2.191)	0.902 (2.906)
Presence of Intranet	-4.19 (2.633)	-0.725 (5.377)
<b>Inverse Mills Ratio (<math>\lambda</math>)</b>	11.756* (3.806)	9.778* (5.669)
R square	0.0938	0.1437

Note – Both regression additionally contains a constant and control service type.

\* Significant at 1%, \*\* Significant at 5% and \*\*\* Significant at 10%

**Table 7B: Counterfactual Estimates for Levels of Technology Integration**

	Level Three (N = 497)	Level Four (N = 124)
<b>If Level Three</b>	42.7 <i>Quadrant II</i>	31.58 <i>Quadrant I</i>
<b>If Level Four</b>	58.6 <i>Quadrant III</i>	50.6 <i>Quadrant IV</i>