MIS Quarterly

RESEARCH ARTICLE

ANTECEDENTS OF INFORMATION SYSTEMS SOURCING STRATEGIES IN U.S. HOSPITALS: A LONGITUDINAL STUDY[1]

Corey M. Angst, Kaitlin D. Wowak, Sean M. Handley, and Ken Kelley

IT, Analytics, and Operations Department, University of Notre Dame, Mendoza College of Business,
Notre Dame, IN 46556 U.S.A.
{cangst@nd.edu} {katie.wowak@nd.edu} {shandley@nd.edu} {kkelley@nd.edu}

The popular press has long used the terms single-sourcing and multisourcing (also known as best of breed) to describe organizations' sourcing strategies. Whereas there is an implicit understanding of these terms, no research has quantified what distinguishes one sourcing configuration from another or what institutional factors contribute to the pursuit of one strategy over the other. We leverage institutional theory to examine how key organizational antecedents such as strategic orientation (mission), formal structure (size), and internal dynamics (patient case mix complexity) influence the rate at which organizations move toward or away from a single-sourcing configuration. Employing longitudinal modeling combined with sequence analysis techniques, we empirically evaluate IS sourcing strategies of nearly all U.S. hospitals operating continuously over a 9-year time frame from 2005 to 2013. We find that hospitals are generally trending toward a single-sourcing configuration and that formal structure and internal dynamics serve as predictors of this trend. Contrary to the predictions of institutional theory, we find that strategic orientation is not predictive of IS sourcing strategy. These results have important implications for research and practice. Notably, we are the first to quantify sourcing strategies, and, by doing so, are able to inform practitioners and academics of the key organizational characteristics that lead hospitals to move more quickly toward single-sourcing configurations.

Keywords: IS sourcing strategy, institutional theory, firm characteristics, electronic medical record systems, health IT, panel data, mixed effects model, longitudinal

Introduction

Should organizations source information systems (IS) from a single supplier (single-sourcing) or from multiple different suppliers (multisourcing)? This is a question that has perplexed managers as there is no universally dominant sourcing strategy in most industries (Elmaghraby 2000). Although sourcing is among the most important strategic decisions organizations face (Gottfredson et al. 2005; Hayes et al. 2005), a review of the literature suggests that little is known about sourcing trends and whether, in a given industry, organizations are migrating toward a single-sourcing or multisourcing configuration. Consequently, our study sets out to (1) assess whether organizations are trending toward one sourcing approach over another, and (2) determine the extent to which organizational antecedents influence the relative rate at which organizations move toward a specific IS sourcing configuration. The first aspect of our study—whether there is a general trend toward a specific sourcing approach—seems fairly straightforward; however, the literature includes only a paucity of empirical findings related to IS sourcing strategies and there is a lack of consensus on the language and terms

[1]Indranil Bardhan was the accepting senior editor for this paper. David Preston served as the associate editor.

The appendix for this paper is located in the "Online Supplements" section of the *MIS Quarterly*'s website (http://www.misq.org).

used. These factors, individually as well as collectively, make it more difficult to identify and quantify what constitutes single-sourcing and multisourcing strategies. For that reason, we first introduce several terms and concepts to establish the context of our research.

In our study, we use the term *IS sourcing*[2] *configuration* to refer to discrete decisions that the organization makes about (1) whether to acquire a given application, and, if so, (2) which supplier is chosen to provide the application. When an organization is choosing to source an enterprise resource planning system (ERP), for instance, it may choose to source its supply chain management module and financial accounting system from SAP®, but then source the customer relationship management system from Salesforce®. Where our study differs from prior work is that we specifically examine how the IS sourcing *configuration* changes over time, and argue that this is more akin to an IS sourcing *strategy* than other studies that do not include a temporal aspect. That is, while IS sourcing configuration reflects the portfolio of software application suppliers at a discrete point in time, IS sourcing strategy is a temporal extension of IS sourcing configuration that takes into account the change in the applications used and the suppliers of each application over time.

At the most basic level, any time one supplier is used to source all applications in a suite in a given year, the organization is using a prototypical single-sourcing configuration. Conversely, when more than one supplier is used to source the applications in a suite in a given year, the organization is using a multisourcing configuration. Whereas it is somewhat straightforward to identify a prototypical single-source configuration in a given year, we contend that empirical assessments of sourcing *strategies* over time are sparse as most studies do not take into account how the strategy evolves (for an exception, see Kelly and Amburgey 1991). It is also important to note that we are interested in an organization's *realized strategy* defined as "a pattern in a stream of decisions" rather than an organization's *intended strategy*, that is, its plan (Mintzberg 1978, p. 934). Specifically, with the aid of a novel longitudinal dataset, we observe the actual purchasing actions taken by organizations, enabling us to assess each organization's realized IS sourcing strategy. That is to say, we examine the actual outcome rather than, for example, surveying procurement officers about their purchasing plans, which would yield an intended strategy. Examining an organization's realized sourcing strategy provides richer and more accurate insights than its intended sourcing strategy and thus is a strength of our research.

The configuration of software application suppliers at each organization can change from year to year. Therefore, our focus is on the rate (relative to other organizations in the same industry) at which an organization moves toward or away from a particular sourcing configuration. Quantifying the degree to which a particular multisourcing configuration deviates from a prototypical single-sourcing configuration requires an analytical assessment that to our knowledge has not been undertaken. Specifically, we are not aware of any prior research that quantifies the degree to which a sourcing configuration deviates from another in a given year or the antecedents of the time-dependent migration toward (or away from) a prototypical single-sourcing configuration. Drawing upon institutional theory, our study strives to address these gaps in the literature by forwarding a shared language for sourcing of modular software applications while simultaneously offering a methodological contribution that addresses shortcomings in prior studies.

To help control for contextual factors which may have a confounding influence on the quantification of sourcing configurations and the identification of their organizational antecedents, our study focuses on a single operating environment: electronic medical record systems (EMRS) in U.S. hospitals. EMRS are information systems that manage patients' electronic medical records (digital versions of a patient's chart) at individual care delivery organizations (e.g., physician practices, clinics, hospitals) allowing "healthcare practitioners to document, monitor, and manage health care delivery" (Garets and Davis 2006, p. 2). EMRS have diffused extensively over the last several years due to both the potential performance advantages they offer and increasingly significant regulatory incentives (IBISWorld 2014). The U.S. market for EMRS was estimated to be $8.8 billion in 2014, with a projected annual growth rate of 6.1% between 2014 and 2019 (IBISWorld 2014). Given that the supply market for EMRS has been characterized as having a low concentration (as of 2013, the top three suppliers, Epic Systems, Cerner, and Meditech, combined for just over 37% of the market) and a high level of competition, the options available to hospitals are numerous (IBISWorld 2014). In addition, EMRS are modular by design. Thus, while suppliers may bundle several modules together, there are opportunities for hospitals to "mix-and-match" suppliers within the same suite. Consequently, EMRS are an ideal context to examine the extent to which hospitals are migrating toward one sourcing approach over another and institutional factors that cause

[2]Unlike prior research (e.g., Ang and Cummings 1997; Goo et al. 2009; Ramasubbu et al. 2008) that has used the phrase *IS sourcing* in the context of insourcing, outsourcing, or offshoring of IS services, our use of IS sourcing does not reflect any aspect of determining the vertical boundaries of the organization or the sourcing of IT-based business services or software development.

certain hospitals to migrate faster or slower than others. Notwithstanding the tremendous growth in the usage of EMRS in practice, extant research paints an ambiguous picture of the value of health IT adoption (Agarwal et al. 2010; Angst et al. 2011). Moreover, although hospitals are increasingly relying on commercial suppliers for health IT (Classen and Bates 2011; Kellermann and Jones 2013), surprisingly little research exists on the sourcing configurations employed for commercial applications (Chaudhry et al. 2006; Goh et al. 2011).

A significant body of scholarly work exists on single-sourcing versus multisourcing in the context of procuring physical products or components of physical products (e.g., Elmaghraby 2000; Li and Debo 2009; Richardson 1993). However, the sourcing of enterprise software applications, such as modules within EMRS suites, is theoretically distinct from sourcing components for physical products, thus limiting the extent to which insights from that literature directly translate to the EMRS context. First, unlike components of physical products which can be simultaneously multisourced (i.e., two different suppliers provide quarter-inch socket head cap screws for a brake assembly), each module within an EMRS suite cannot have more than one supplier at any given point in time (i.e., simultaneous parallel applications do not exist in the EMRS context). Second, when sourcing commercially available EMRS, hospitals face heterogeneous supplier products, which complicate direct comparison. When sourcing physical products, suppliers often (but not always) compete on how well they can produce products to the customer's exact specifications. The customer controls the design, thus comparison across suppliers is with regard to a homogenously designed product. With EMRS applications, each supplier's software is different (i.e., heterogeneous) albeit with some degree of customization possible. Finally, integration and interoperability across modules within the EMRS suite can fundamentally impact workflows, process performance, and patient–provider interactions (Brailer 2005; Kumar and Aldrich 2010). Therefore, sourcing decisions within the EMRS context must take into account much broader organizational and operational factors such as workflow redesign, training, etc. While component integration within a product certainly has implications for overall product performance, sourcing decisions for individual components of a product do not typically have such broad organizational implications. For these reasons, we seek to develop a novel theoretical framework related to the sourcing of software modules, which necessitates methodological developments on the measurement of sourcing and application of advanced longitudinal modeling procedures.

We utilize a longitudinal modeling framework to examine EMRS sourcing configurations at all U.S. hospitals that operated continuously over a 9-year timeframe from 2005 to 2013. Our study makes three primary contributions. First, our results indicate that, in general, hospitals are moving toward single-sourcing, but certain institutional factors are accentuating or attenuating the rate of this migration. We provide theory-based explanations for why this migration toward single-sourcing is happening. Second, we quantitatively measure the extent to which a hospital's sourcing configuration deviates from a prototypical single-sourcing configuration. Measuring the degree of deviation provides richer insights than dichotomously classifying hospitals as either using a single-sourcing or a multisourcing configuration and as, we discuss below, is more precise than simply counting the number of suppliers used. Finally, our comprehensive longitudinal analysis allows us to capture a dynamic view of how sourcing strategies are evolving and how certain types of hospitals are pursuing single-sourcing at either a faster or slower rate than the industry at large. We believe that the use of sequence analysis in a longitudinal framework for assessing change can be applied across a broad range of sourcing environments.

Background and Research Context

Electronic Medical Record Systems

As previously noted, EMRS are central to a hospital's information technology portfolio. While empirical results have been mixed, the preponderance of evidence suggests that EMRS can provide numerous operational benefits including enhanced patient tracking and monitoring, improved quality of care, higher levels of clinician and administrative efficiency, better capital resource utilization, and quicker provision of care (Agha 2014; Buntin et al. 2011; HealthIT.gov 2015; Kalorama Information 2014; Lee et al. 2013; McCullough et al. 2010). An EMRS is an application environment that is composed of multiple distinct, yet interrelated modules. This environment supports the patient's electronic health record across inpatient and outpatient environments, and is used by healthcare practitioners to document, monitor, and manage healthcare delivery. For the purpose of this study, we include the five most commonly adopted modules that make up the EMR category as defined by HIMSS Analytics, excluding the sparsely populated physician and patient portals, which were added in 2008 and 2011, respectively. The following definitions came from a subscription-based, proprietary database (HIMSS Analytics 2015):

- ***Clinical Data Repository (CDR)***: A centralized database that allows organizations to collect, store, access, and report on clinical, administrative, and financial information collected from various applications within or across the healthcare organization.

- ***Clinical Decision Support System (CDSS)***: An application that uses preestablished rules and guidelines, that can be created and edited by the healthcare organization, and integrates clinical data from several sources to generate alerts and treatment suggestions.

- ***Computerized Practitioner Order Entry (CPOE)***: An order entry application specifically designed to assist clinical practitioners in creating and managing medical orders for patient services or medications.

- ***Order Entry*** (including order communication): An application that allows for entry of orders from multiple sites including nursing stations, selected ancillary departments, and other service areas; allows viewing of single and composite results for each patient order.

- ***Physician Documentation***: This software documents notes that describe the care or service to a patient.

Defining Sourcing Configurations

As noted earlier, we specifically compare sourcing configurations used in each year and extrapolate this data longitudinally to test hypotheses about the rate at which hospitals are pursuing a particular sourcing strategy. The sourcing approach in a given year constitutes the nexus of a collection of decisions, such as to make (develop in-house) or buy (contract externally), which supplier (or suppliers) to select, contract duration, governance system (relational and/or contractual), and so forth. In this study, we focus on how many suppliers to use when sourcing an EMRS suite. Given that each module within an EMRS suite can only be sourced from a single supplier at any given time, if all the modules within a suite are provided by the same supplier, the hospital is using a prototypical single-sourcing configuration at the EMRS suite level (see Figure 1, diagram A). Alternatively, if more than one supplier is used to source modules within the EMRS suite, the hospital is using a multisourcing configuration at the EMRS suite level. The most extreme multisourcing configuration is when each module is provided by a different supplier (see Figure 1, diagram B for an illustration of this configuration). Hereafter, when referring to single-sourcing and multisourcing of EMRS, we are referring to the *suite level* sourcing configuration or strategy.

We conceptualize EMRS sourcing configurations as *the degree to which a hospital deviates from the prototypical single-sourcing configuration* (see Figure 1, diagram A). We anchor on single-sourcing not because of any *a priori* expectations of performance advantages of single-sourcing, but simply for empirical reasons. Specifically, quantifying the degree to which two sourcing configurations differ is a nontrivial problem (especially when taking a longitudinal perspective) and thus we need to have a standard against which we compare configurations. By quantifying sourcing configurations, we are able to develop an empirically grounded understanding of realized EMRS sourcing practices and delve deeper into the sourcing strategies employed over time. As we discuss in more detail below, while simply counting the number of suppliers is empirically appealing, it is not a precise means of analyzing sourcing configurations.

Comparative Advantages of Single-Sourcing and Multisourcing Configurations

Although we are primarily interested in why hospitals migrate toward (or away from) single-sourcing, it is important to understand the advantages of single-sourcing versus multisourcing as it relates to why we would expect hospitals in differing institutional contexts to migrate toward single-sourcing strategies more quickly, more slowly, or not at all. Neither single-sourcing nor multisourcing can be established as an indisputable "best practice" as each offers advantages and disadvantages (see Table 1). First, we specify the advantages of single-sourcing recognized in the literature. Single-sourcing information systems, such as EMRS, allows hospitals to develop long-term relationships with a small set of suppliers, which reduces the risk of opportunistic behavior on the part of suppliers (Deming 1986; Richardson and Roumasset 1995) and allows hospitals to consolidate their spending to realize economies of scale, better leverage their purchasing power, and minimize total transaction costs (Dyer 1997). Another benefit of single-sourcing information systems is ease of implementation. Hospitals do not have to worry about integrating different modules from various suppliers, which facilitates the adoption process and keeps costs to a minimum (Ford et al. 2013). Conversely, multisourcing complicates the implementation of new software releases, which can delay enhanced functionality and increase costs (Roskill 2014). Thus, implementation and upgrade difficulties result, at least in part, from the interrelated nature of the different EMRS modules. Interdependent tasks carry a heavier coordination burden, which is exacerbated when multiple suppliers are involved (Bapna et al. 2010). This interdependency across suppliers obscures performance assessment, weakening the viability of formal incentive mechanisms (Bapna et al. 2010). Multisourcing also requires that a hospital's IT staff has expertise in managing and integrating diverse modules that may employ dissimilar software and database platforms (Ford et al. 2013). Finally, employing a multisourcing approach can introduce interdepartmental compatibility issues where technologies across departments may not communicate well with each other, increasing coor-

Figure 1. Single-Sourcing and Multisourcing Configurations at Discrete Points in Time

Table 1. Comparative Advantages of Single-Sourcing and Multisourcing Strategies

Literature on Sourcing IT	Single-Sourcing	• Facilitates implementation; hospitals do not have to worry about integrating different modules from various suppliers, which minimizes adoption costs (Ford et al. 2010). • Eliminates the need to integrate modules from different suppliers, which minimizes total transaction costs (Bapna et al. 2010; Ford et al. 2010). • IT staff can develop specialized knowledge of one application (Ford et al. 2013; Ford et al. 2010). • Eases performance assessment and use of formal incentive mechanisms (Bapna et al. 2010). • Facilitates the installation of new software releases, which enhances functionality (Roskill 2014). • Reduces department silos and facilitates potential synergies between functions (Bapna et al. 2010). • Eliminates the need for staff to input data multiple times (Bapna et al. 2010; Roskill 2014). • Lower learning curve (all modules within a suite have similar interfaces) (Ford et al. 2010). • Long-term buyer–supplier partnerships foster loyalty and trust (Burke et al. 2007; Costantino and Pellegrino 2010; Deming 1986; Mishra and Tadikamalla 2006). • Reduces risk of opportunistic behavior by either entity (Costantino and Pellegrino 2010). • Facilitates the deployment of specialized resources aligned with the unique needs of the buying firm and thereby improving quality (Deming 1986; Richardson 1993). • Buyers consume fewer resources overseeing and policing their supply base, which minimizes total transaction costs (Burke et al. 2007; Dyer 1997; Richardson and Roumasset 1995). • Allows the buying firm to consolidate its spending, allowing it to realize economies of scale and better leverage its purchasing power (Bozarth et al. 1998; Burke et al. 2007; Mishra and Tadikamalla 2006).
	Multisourcing	• Hospitals can select the "best" modules that are closely aligned with the unique requirements of individual operating units or preferences of clinical staff, which eliminates the need to reengineer business processes (Ford et al. 2010; Karim et al. 2007; Ray et al. 2005; Silva and Hirschheim 2007). • Lower switching costs (Elmaghraby 2000; Ford et al. 2010; Mishra and Tadikamalla 2006). • Permits individual units to upgrade or replace modules as they see fit (Ford et al. 2010). • Increases a hospital's overall IT flexibility, which allows it to use its IT systems as a competitive advantage (Deeter 2013). • Diversifies supply base and thus firms are not particularly dependent on any single supplier (Burke et al. 2007; Costantino and Pellegrino 2010; Larson and Kulchitsky 1998). • Limits the power of any single supplier (Burke et al. 2007; Porter 1985). • Fosters competition among potential suppliers and can assure the buyer receives a competitive price and high-quality service (Berger et al. 2004; Porter 1985; Richardson and Roumasset 1995).

dination costs and reducing synergies or efficiencies between functions (Jenkins 2015).

While sourcing through a single supplier has advantages, it also comes with limitations compared to multisourcing. For example, multisourcing allows hospitals to select EMRS modules that are closely aligned with the unique requirements of individual operating units or preferences of clinical staff. By allowing different units to select the technology that best facilitates their existing processes, it reduces the need to reengineer business processes in order for them to align with the technology's capabilities (Ray et al. 2005), which is often the case with single-sourcing (Ford et al. 2010). This is also one of the reasons why multisourcing is often referred to as "best of breed" (Deeter 2013; Light et al. 2001; Roskill 2014). Another advantage of multisourcing is that it permits individual units to upgrade or replace modules as they see fit (Ford et al. 2010); this is a significant benefit as it increases the hospital's overall flexibility and allows the hospital to use IS as a competitive advantage (Deeter 2013). Finally, multisourcing fosters competition among suppliers, which can reduce the chance of suppliers feeling a sense of entitlement and can ensure that they do not eschew responsibilities (i.e., shirk).

To summarize the foregoing discussion, there are clear advantages and disadvantages to both single-sourcing and multisourcing. Against this backdrop, we seek to explicate the prevailing forces that are influencing the trajectories of EMRS sourcing configurations being pursued by hospitals. In the next section, we introduce institutional theory and establish the theoretical underpinning for our research hypotheses.

Theory and Hypothesis Development ■

Institutional Theory

Institutional theory serves as our overarching framework describing why hospitals' sourcing decisions change over time and what factors lead to the pursuit of a long-term IS sourcing strategy. Institutional logic is used to explain why organizations eventually mimic the strategies of others within their peer group (DiMaggio and Powell 1983). This trend toward isomorphism (i.e., organizational similarity) is not driven by performance improvements alone (D'Aunno et al. 1991; Scott 1987), but also pressures for *legitimacy* (Boxenbaum and Jonsson 2008; D'Aunno et al. 1991; Sherer and Lee 2002). Legitimacy is defined as "a generalized perception or assumption that the actions of an entity are desirable, proper, or appropriate within some socially constructed system of norms, values, beliefs, and definitions" (Suchman 1995, p. 574). In other words, institutional theory suggests that organizations face pressures to conform to peer group norms. Increasingly an institutional perspective is also leveraged to understand why industrial sectors differ in their pace of change and to explicate the heterogeneity across organizations within a sector in terms of the rate of change (Dacin et al. 2002; Greenwood and Hinings 1996; Pache and Santos 2010; Sherer and Lee 2002). As our primary theoretical interest is in explaining why different types of hospitals are trending toward (or away from) single-sourcing at varying rates, drawing on this institutional logic is a natural fit. Hospitals, like all organizations, seek legitimacy from their peers and thus often adopt managerial practices or mimic strategies exhibited by others, which results in entities acting similarly over time (Sherer and Lee 2002). However, as we specify below, hospitals are not homogeneous in terms of their peer group. As a consequence, hospitals are likely to vary with regard to the institutional pressures they face for legitimacy and conformance to peer group norms for sourcing IS.

According to institutional theory, organizational decisions are guided by two important dimensions: technical and institutional (Vibert 2004). The technical dimension centers on the operations and technology required for day-to-day processes or procedures whereas the institutional dimension interfaces with the public and is most visible to outsiders. These dimensions potentially produce competing pressures; the technical aspect is governed primarily by efficiency considerations while the institutional dimension is guided more by expectations or norms from the external environment (Greenwood and Hinings 1996; Vibert 2004). In hopes of gaining legitimacy from stakeholders and other outsiders, hospitals often place more emphasis on conforming to institutional pressures (D'Aunno et al. 1991; Scott 1987).

Institutional theory suggests that organizations' pressures for legitimacy depend on various organizational factors such as an entity's mission and size as well as the internal dynamics of the organization (Baum and Oliver 1991; Greenwood and Hinings 1996). Indeed, the factors of mission and size have been utilized in prior studies applying institutional logic in a hospital context (e.g., Ruef and Scott 1998). More recent work recognizes that fully understanding how and why organizations respond differently to similar external institutional pressures requires consideration of internal dynamics, or the processes, policies, resources, etc. within an organization (Pache and Santos 2010). For our research, we consider two key dimensions of a hospital's mission (what we refer to as *strategic orientation*)—for-profit versus not-for-profit and teaching versus non-teaching—as well as two dimensions of its *formal structure* (Meyer and Rowan 1977)— hospital size and health system size. A salient determinant of a hospital's intra-organizational processes, policies, and resources (i.e., internal dynamics) is its patient and operational complexity (Angst et al. 2011; Sturgeon 2007). Therefore, for *internal dynamics*, we consider a common dimension of hospital complexity, namely patient case mix complexity, which has been defined as an indicator of the complexity of procedures and the severity of complications within patients (Sturgeon 2007).

Another key premise of institutional theory is that isomorphism takes time, and to capture a holistic understanding of the pace of conformance in regard to sourcing strategy, one must adopt a longitudinal perspective (Scott 1987). Thus, in the following sections, we propose hypotheses that test the impact of time and each of the hospital factors outlined above (see Figure 2 for a conceptual model of the relationships hypothesized). We argue that these factors relate to the year-over-year change in sourcing configuration, thus resulting in a *slope* or *trend* relative to the degree of single-sourcing. We believe this to be more indicative of the temporal and changing nature of sourcing configurations than sampling a particular year, which may be atypical of the overall sourcing strategy across years. As noted earlier, we compare all sourcing configurations to single-sourcing (as opposed to multisourcing) for empirical reasons and because recent research suggests that hospital administrators believe that single-sourcing is emerging as the dominant strategy (Ford et al. 2013). Anecdotally, our informal discussions with health IT professionals were also reflective of this trend. To be clear, we are not arguing that a single-sourcing strategy leads to superior performance. Rather, observing that there appears to be a general trend toward single-sourcing, we seek to understand if and how institutional factors drive a hospital toward (or possibly away from) single-sourcing at a quicker or slower rate.

Hospital Strategic Orientation

In this section, we propose that a hospital's strategic orientation will impact the rate at which it pursues a single-sourcing IS strategy. We examine two hospital characteristics (for-profit/not-for-profit and teaching/non-teaching) related to strategic orientation and discuss how they may affect migration toward a single-sourcing strategy.

For-Profit Versus Not-for-Profit

All hospitals are embedded in both patient care and business logic to varying extents as dictated by the business model of for-profit (FP) or not-for-profit (NFP). Both FP and NFP hospitals are driven by cost considerations, and given that research on enterprise resource planning (ERP) systems suggests that single-sourcing should reduce overall costs (Ehie and Madsen 2005), we believe that FP and NFP hospitals will both migrate toward single-sourcing, but will do so at differing speeds. FP hospitals often have more slack resources than NFP hospitals as they have private investors, offer more profitable services, and have the ability to raise capital (Becker 2014; Joynt et al. 2014), any or all of which can facilitate technology upgrades or changes in sourcing configurations. Indeed, this surplus of resources gives FP hospitals more flexibility in regard to their sourcing strategy as they have the means to adopt new technologies and/or change suppliers of existing technologies much more easily (and faster) than NFP hospitals. If and when NFP hospitals decide to change sourcing strategy, they are potentially unable to raise the necessary capital from shareholders as quickly as FP hospitals can, but must slowly accumulate the resources internally over time. FP hospitals also face institutional pressures to maximize returns to outside investors and thus may place more emphasis on adhering to expectations or norms from their external environment faster than their NFP counterparts (Greenwood and Hinings 1996; Ruef and Scott 1998; Vibert 2004). Similarly, FP hospitals could be competing for resources from a common pool of investors and thus may trend toward isomorphism faster than NFP hospitals as a way to secure outside resources. Therefore, we hypothesize:

> *Hypothesis 1: For-profit hospitals will migrate toward a single-sourcing strategy more* ***quickly*** *than will not-for-profit hospitals.*

Teaching Versus Non-Teaching Hospitals

The strategic orientation of a hospital also varies depending on whether it is a teaching or non-teaching hospital. In addition to caring for patients, teaching hospitals are also responsible for educating the next generation of healthcare practitioners and conducting research. Indeed, rigorously training future physicians is paramount at teaching hospitals. If future physicians learn to take shortcuts or employ work-arounds while caring for patients in order to accommodate a technology's limitations, they may learn to deliver suboptimal medical care. Similarly, if physicians are required to reengineer their research processes (as is more often the case with a single-sourcing strategy) (Ford et al. 2010) to accommodate a technology's capabilities, it could hinder their research efforts and restrict the development of the field at large.

Because teaching hospitals are tasked with training future physicians who have specialized skills and focused research objectives, they often develop a narrower focus of expertise (i.e., they become "specialists" in a particular discipline), which likely impacts whether and how they respond to institutional pressures compared to their non-teaching counterparts

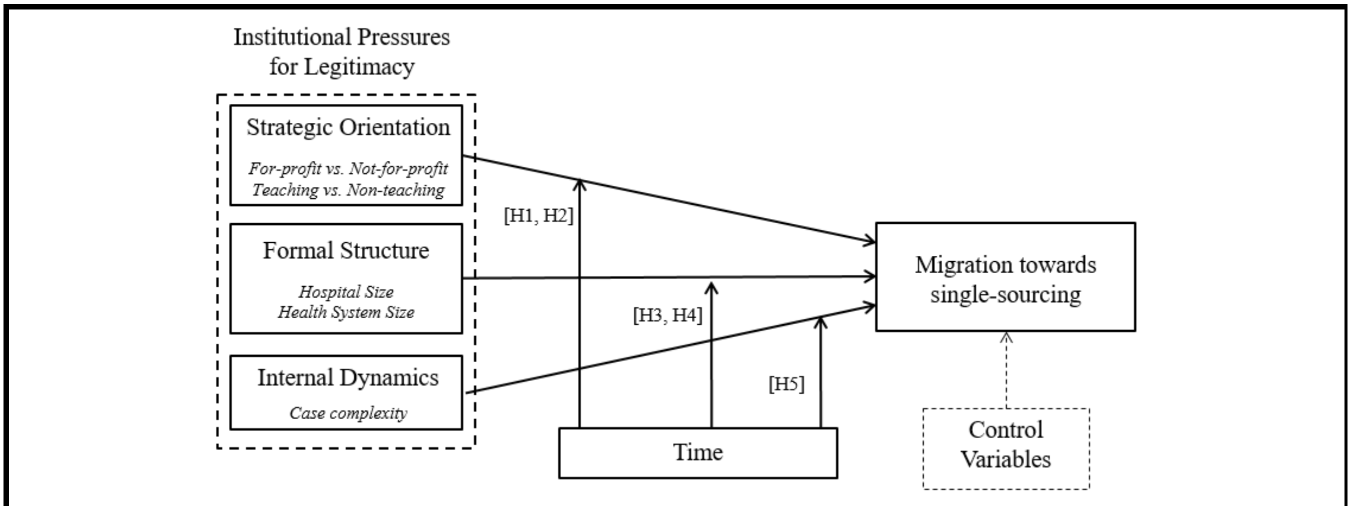


Figure 2. Conceptual Model

(Ruef and Scott 1998; Scott 1987). The more specialized a teaching hospital and its physicians become, the less institutional pressures it may face due to the limited number of corresponding hospitals that possess similar distinctive competencies (Ruef and Scott 1998). Consequently, we argue that, over time, teaching hospitals will be less attentive to external institutional pressures that are driving other non-peer hospitals to adopt particular practices and will instead place more emphasis on the technical dimension that centers on technology required for efficient day-to-day processes and procedures (Greenwood and Hinings 1996; Ruef and Scott 1998). As such, we advance that teaching hospitals will migrate more slowly toward a single-sourcing strategy because multisourcing allows specialized physicians, who are typically more influential, to select the best technology for the unique requirements of their operating units. Stated slightly differently, in a teaching hospital context, the advantages of multisourcing are expected to be more pronounced, which would make these hospitals more reticent to adopt a single-sourcing approach even if that is the broader trend in the industry. Therefore, we hypothesize:

> *Hypothesis 2: Teaching hospitals will migrate toward a single-sourcing strategy more* ***slowly*** *than will non-teaching hospitals.*

Hospital Formal Structure

In this section, we hypothesize that two characteristics of a hospital's formal structure (Kelly and Amburgey 1991)—hospital size and health system size—influence the rate at which it pursues a single-sourcing IS strategy.

Hospital Size

Institutional theory and the technology adoption literature each present conflicting arguments regarding the relationship between organization size and innovation adoption. On the one hand, as organizations become larger, they often struggle with the increased complexity that comes with managing a multitude of resources (Dobrev et al. 2003; Hannan and Freeman 1977). Further, larger organizations typically encounter more resistance to change or organizational inertia from having a hierarchical organizational structure, which produces decision making and communication delays (Dobrev et al. 2003; Hannan and Freeman 1977; Kelly and Amburgey 1991; Sherer and Lee 2002; Zhu et al. 2006).

On the other hand, larger organizations typically have more slack resources, which enable them to evaluate the pros and cons of moving to a new strategy and allow them to modify their sourcing approach, if desired (Rogers 2003; Sherer and Lee 2002; Zhu et al. 2006). This is consistent with the argument presented by Greenwood and Hinings (1996) that organizations with a greater capacity for action (grounded in the availability of competencies and resources) are expected to be capable of enacting change more quickly. While it may be costly to acquire an entirely new EMRS suite, larger hospitals have the resources to do so and may view this as an investment to streamline data exchange between modules, which can be particularly challenging when modules are sourced from multiple suppliers. Larger organizations are also argued to be more capable of absorbing innovation adoption difficulties (Damanpour 1996). Therefore, while it can be disruptive when organizations change their sourcing strategy, larger hospitals may be more willing to take a short-term interruption associated with transforming a system to single-source with the promise of fewer disruptions in workflow and overall lower training and implementation costs in the long-term.

To summarize, a review of the literature reveals arguments for both a positive and a negative association between organization size and innovation adoption. However, a meta-analysis of this relationship found that, all else being equal, the net relationship between organization size and the adoption of technology and process innovations is positive (Damanpour 1992). Therefore, while we recognize the counterarguments, we propose the following hypothesis:

> *Hypothesis 3: Larger hospitals will migrate toward a single-sourcing strategy more* ***quickly*** *than will smaller hospitals.*

Hospital Health System Size

The size of the health system to which a hospital belongs may also impact its EMRS sourcing strategy. Specifically, it is expected that hospitals that are members of larger health systems will move more quickly toward a single-sourcing strategy for several reasons. First, when hospitals are part of larger health systems they may feel more pressure to adhere to institutional norms of the system or practices/strategies exhibited by others in their network. Consistent with the "safety-in-numbers effect" (Ahmadjian and Robinson 2001), no hospital wants to be the only hospital not adopting a particular strategy or the last hospital in the health system to do so, and thus hospitals may give way to institutional pressures (over technical pressures) in hopes of gaining legitimacy from stakeholders and other hospitals in their health system. When hospitals are part of smaller health systems, however, they have fewer peer hospitals to benchmark against and thus may face less institutional pressures due to the limited number of corresponding hospitals in their network.

Second, larger health systems may wish to standardize across facilities in order to reduce costs related to IT training, qualification testing, and technical support and thus there may be a system-wide initiative for hospitals to migrate toward a particular sourcing approach (Angst et al. 2010). Consequently, hospitals in larger health systems may receive more guidance and/or IT support about how to alter their sourcing strategy more efficiently and faster than hospitals in smaller health systems that often have fewer resources. As a result, we believe centralization increases the likelihood that hospitals in larger health systems will follow corporate directives and will do so faster than hospitals in smaller health systems. Even in the absence of corporate guidelines, institutional theory suggests that organizations follow the actions of their peers—in this case other hospitals within similarly sized health systems (Angst et al. 2010; DiMaggio and Powell 1983). As a result, we anticipate that hospitals that are part of larger systems will move more quickly toward single-sourcing. Therefore, we hypothesize:

> *Hypothesis 4: Hospitals that are members of larger health systems will migrate toward a single-sourcing strategy more* ***quickly*** *than will hospitals that are members of smaller health systems.*

Hospital Internal Dynamics

Case Mix Index

According to institutional theory, it is "necessary to take seriously the internal complexity of organizations" in order to understand why organizations emphasize technical pressures over institutional pressures and vice versa (Greenwood and Hinings 1996, p. 1033). Specifically, institutional theory acknowledges that organizations often handle internal complexity by differentiating into groups (functions) that focus on a specialized tasks (e.g., cardiology, neurology, oncology, critical care) (Greenwood and Hinings 1996). This process of task specialization often results in considerable differences in needs or requirements among groups (Greenwood and Hinings 1996), which is more conducive to multisourcing and thus suggests a slower migration toward single-sourcing. We therefore expect the complexity of patient cases to accordingly influence a hospital's sourcing strategy.

Case complexity is often measured by a hospital's case mix index (CMI) defined as "the variations in resource requirements associated with the treatment of different types of patients" (Rosko and Chilingerian 1999, p. 58). Specifically, hospitals with a higher CMI treat patients with more diverse and clinically complex needs than hospitals with a lower CMI. Hospitals that have a higher CMI (e.g., the Cleveland Clinic or Mayo Clinic) need the best-available technology for each function in order to properly diagnose and treat patients with complex conditions, which suggests that a multisourcing strategy may be advantageous, and thus high CMI hospitals may be slow to migrate toward single-sourcing. Similarly, these hospitals need a high-degree of IT flexibility so individual operating units can upgrade or replace EMRS modules as they see fit in order for them to continuously have the most sophisticated patient care capabilities. Hospitals with a high CMI are focused primarily on treating complex cases and thus cannot afford to reengineer business processes in order to fit a technology's capability—again favoring multisourcing or at least a slower migration to single-sourcing. Finally, the clinical staff in hospitals with high CMI may also recognize the need to implement the best technology for each function and thus may be more receptive to adopting modules from different suppliers even if it requires more training.

If hospitals with high internal complexity (high CMI) attempt to implement a single-sourcing approach too quickly, it could bring about dissatisfaction with how each group's interests are treated and thus be detrimental for the entire hospital. Therefore, we hypothesize:

> *Hypothesis 5: Hospitals with more complex cases (i.e., higher case mix index) will migrate toward a single-sourcing strategy more* ***slowly*** *than will hospitals with less complex cases.*

Methods

In this study, we test our hypotheses by examining the temporal integration and trajectory (i.e., the degree of single sourcing over time) of five modules into an EMRS suite and the suppliers associated with these applications. We chose to test our hypotheses in this context because there are a finite number of modules (5) included in an EMRS suite and a manageable number of suppliers that provide these applications (there were 107 suppliers across all modules over the 9-year period). We combined data from two sources to construct our data set, which is a longitudinal panel: (1) a nationwide, annual survey of care delivery organizations in the United States, conducted by HIMSS Analytics™ (HA); and (2) HospitalCompare, a publicly available database provided by the Centers for Medicare and Medicaid Services. Figure 3 provides evidence of the number of integrations per year by module and the increasing trend of adoption over time across hospitals. As previously noted, we are interested in a hospital's realized sourcing strategy (rather than its intended sourcing strategy) and thus we considered the actual number of suppliers from which a hospital sources EMRS modules.

We eliminated hospitals that did not operate in every year of our sample from 2005 to 2013. We also excluded hospitals that did not adopt any or only adopted one module in the EMRS, as the sourcing of fewer than two is not indicative of a sourcing strategy and could bias our results. The number of hospitals in any given year varies from 3,983 to 5,420, with 3,417 hospitals having two or more EMRS modules coinciding in each year of our data, with some variation due to missing data (depending on the model, our sample size ranges from 2,824 to 3,417).

We used a type of sequence analysis to assess the different sourcing strategies hospitals employ. Sequence analysis techniques are becoming more popular in the social sciences because they provide researchers with a means to investigate a host of research questions. Specifically in the health IT domain, Adler-Milstein et al. (2014) found that the order of adoption of electronic health record modules is a function of policy mandates and hospital characteristics. Angst et al. (2011) found that the integration sequence of cardiology IT is related to hospital performance. Others have used these temporally ordered sequence methods to analyze sociomaterial routines (Abbott 1983; Gaskin et al. 2014), variety in work processes (Pentland 2003a, 2003b), and implementation processes related to IS development (Sabherwal and Robey 1993).

Sequence analysis has advantages over discrete counts of the numbers of suppliers used in a suite. This technique allows us to distinguish between hospitals with the same number of suppliers, or with modules that are not implemented. For example, assume hospital 1 uses this sourcing approach with each letter representing a supplier for a module in the EMRS suite: A-A-A-B-C; and hospital 2 uses this sourcing configuration: A-A-B-B-C. If we simply counted the number of suppliers for both hospitals, it would appear as if they use the same sourcing configuration as both hospitals source modules from three suppliers; this is clearly not the case and thus counting the number of suppliers could lead to inaccurate conclusions. By using a sequence analysis technique, we are able to determine that hospital 1's approach is closer to a prototypical single-sourcing configuration than hospital 2's, and we can quantify this difference (we discuss the sequence algorithm in the next section).

From HA, we captured the modules that were integrated into the EMRS, the associated suppliers who provided the modules, and the contract year (i.e., when the module was implemented), and then constructed the patterns of implementation (sequences) over time. We quantify the sequence empirically assessing the similarity between sourcing configurations as represented by the suppliers that are used for specific modules over time. These sequences form the outcome (dependent) variable in our model. Once the sequences are constructed for each hospital's EMRS in each year, we empirically test how similar each is to a prototypical single-sourcing strategy.

Construction of the Closeness to Single-Sourcing Variable

The first step in comparing sequences of ordered events is the construction of the sequences themselves. In Table 2, we illustrate how our sequences were constructed. We devised a novel method that quantifies the extent to which a given

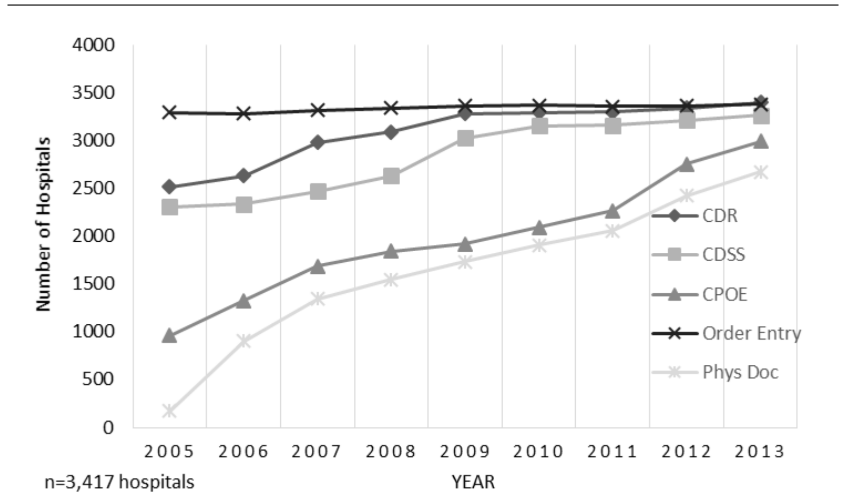


Figure 3. EMRS Module Integration by Year

Table 2. Sourcing Sequence Comparisons

	Hospital SS		Hospital 1		Hospital 2		Hospital 3	
Year	Pure Single Sourcing	Empirical Sequence	Actual Sourcing Configuration	Empirical Sequence	Actual Sourcing Configuration	Empirical Sequence	Actual Sourcing Configuration	Empirical Sequence
2005	As|As|As|As|As	AAAAA	Ep|Ep| – |Ep|Ep	AA–AA	Cn|Cn|Cn|Cn|Cn	AAAAA	Sd|Sd|Sd| – |Sd	ZZZ–Z
2006	As|As|As|As|As	AAAAA	Ep|Ep| – | – |Ep	AA– –A	Cn|Cn|As|As|Mt	AABBC	Mc|Sd|Sd| – |Sd	AZZ–Z
2007	As|As|As|As|As	AAAAA	Mt|Mt| – | – |Mt	AA– –A	Cn|Mc|As|As|Mt	BCAAD	Mc|Sd|Sd| – |Sd	AZZ–Z
2008	As|As|As|As|As	AAAAA	Mt|Mt| – | – |Mt	AA– –A	As|Mc|As|As|Mt	ABAAC	Mc|Sd|Sd| – |Sd	AZZ–Z
2009	As|As|As|As|As	AAAAA	Mt|Mt|Mt|Mt|Mt	AAAAA	As|Mc|As|As|Mt	ABAAC	Mc|Sd|Sd| – |Sd	AZZ–Z
2010	As|As|As|As|As	AAAAA	Mt|Mt|Mt|Mt|Mt	AAAAA	As|Mc|As|As|Mt	ABAAC	Mc|Sd|Sd| – |Sd	AZZ–Z
2011	As|As|As|As|As	AAAAA	Mt|Mt|Mt|Mt|Mt	AAAAA	As|Mc|As|As|Mt	ABAAC	Mc|Mc|Mc| – |Sd	AAA–Z
2012	As|As|As|As|As	AAAAA	Mt|Mt|Mt|Mt|Mt	AAAAA	As|Mc|As|As|Mc	ABAAB	Mc|Mc|Mc|Mc|Sd	AAAAZ
2013	As|As|As|As|As	AAAAA	Mt|Mt|Mt|Mt|Mt	AAAAA	As|Mc|As|As|Mc	ABAAB	Mc|Mc|Mc|Mc|Sd	AAAAZ

The five modules of the EMRS are ordered as follows: Clinical Data Repository | Clinical Decision Support System | Computerized Practitioner Order Entry | Order Entry | Physician Documentation
Suppliers: Allscripts = As, Epic = Ep, Cerner = Cn, Meditech = Mt, McKesson = Mc, Self-Developed = Sd, – = Not implemented

sourcing configuration is close to a single source configuration, eliminating the need to create clusters or categories of sourcing configurations (each of which would ignore information). Clustering is a categorical approach to dealing with what is a quantitative phenomenon in our context, and thus our continuous variable of closeness to single-sourcing provides more insight. Specifically, we created a "target" sequence—a prototypical single-sourcing configuration (as represented by *Hospital SS* in Table 2), where each module in the EMRS was provided by the same supplier in a given year and across all years. Creating a target sequence provided a straightforward way of calculating the numeric distance between each hospital's sequence and this prototypical sourcing configuration. Because the actual supplier does not matter with regard to the sourcing configuration, we coded the dominant supplier in each year as "A," the second most prevalent as "B," and so forth, which allowed us to reduce the unique labels in the sequences. In situations where there were "ties" (i.e., two suppliers provided the same number of modules, see *Hospital 2*, year 2006 in Table 2), we consulted the sourcing configuration in the prior year; the supplier that was dominant in the prior year was then coded as "A" in the following year. When ties were not coincident with prior year suppliers, the first supplier in the sequence was coded as "A."

Importantly, we extended this coding scheme to account for situations in which one supplier overtook another as the dominant supplier in subsequent years. For example, in *Hospital 2*, Allscripts overtook Cerner in 2007 to become the dominant supplier with two of the five modules (see Table 2). This change in sequence labels (e.g., Cerner becomes "B" and Allscripts "A") is appropriate (and accounted for) in our analysis. Because our research question focuses on sourcing configurations (rather than supplier switching, for example), the dominant supplier is always "A." Thus, hospitals are pairwise-compared in each year, first at the level of the dominant supplier (i.e., the frequency and sequence of the "A's") and next at the second most common supplier level (i.e., the frequency and sequence of the "B's"), and so on. This is akin to a standardization process that allows us to compare hospitals not based on the suppliers they choose, but instead based on the sourcing configuration of the modules chosen. Finally, we coded internally developed software (self-developed) modules as "Z" to create distance from a prototypical single-sourcing configuration.

We compare sequence similarities using a matching algorithm as applied through the *adist* function in the statistical program R (R Core Team 2016). The *adist* function calculates a generalized Levenshtein distance (Levenshtein 1966), and assesses the lowest possible weight for number of insertions, deletions, and substitutions needed to transform one sequence into another (see the appendix for additional details). Previous research has shown the Levenshtein distance to be an appropriate tool for measuring similarity of sequences (Abbott and Forrest 1986; Abbott and Hrycak 1990; Spaulding et al. 2013). In our context, every hospital receives a score based on how many *moves* it would take to transform its sequence into the prototypical single-sourcing sequence, with higher scores indicating greater similarity (i.e., fewer moves needed to transform one sequence into another). The *adist* function uses a dynamic programming algorithm to quantitatively compare pairwise sets of sequences (R Core Team 2016). It examines multiple ways to transform one sequence to another and provides the highest score possible for a particular sequence pair. We then performed another calculation to create a distance measure (scaled from 0 to 1 by dividing by the number of modules actually adopted in a given year) from the focal sequence to the prototypical single-source sequence. A value of 1 indicates a perfect match with a prototypical single-sourcing sequence. These distance values, which we refer to as *closeness to single-sourcing*, are the dependent variables in our model.

Antecedents of Migration Toward a Single-Sourcing Strategy

We test five variables and their interaction with time as predictors of the *trend* toward single-sourcing. Importantly, each of these antecedents is modeled as a time-varying variable in that it is allowed to change over the course of the 9 years. Of the strategic orientation variables, hospital mission is coded as FP or NFP (1 or 0), and teaching or non-teaching (1 or 0) as established by the Council on Teaching Hospitals and Health Systems.[3] We use two hospital formal structure variables, which are coded as follows: (1) hospital size (the natural log of the number of staffed beds), and (2) health system size (the natural log of the number of hospitals that are part of the focal health system). We use the log for the various size measures to reduce large differences and increase smaller differences, as is commonly done in such situations. Finally, the proxy for internal dynamics—case mix index—is used to capture and normalize the complexity of the cases that are handled by individual hospitals (see Table 3). Case mix index is widely used in the literature as an indicator of clinical complexity for hospitals and is useful for normalizing patient care-related measures which may vary across hospitals (Fetter et al. 1980). Empirically it reflects the mix of patients in higher versus lower severity diagnosis-related groups (DRGs), with higher CMI indicating more complex cases (i.e., cases involving patients with comorbidities, rare diseases, and/or difficult-to-treat conditions).

Control Variables

As we discuss in the "Analysis and Results" section, mixed effects models provide several advantages over simpler analysis strategies such as OLS regression. One noteworthy benefit of mixed effects models is that they allow for the use of time-variant and time-invariant covariates within the same model. This allows researchers to control for effects that are not of interest from a theoretical standpoint, but for which the effects need to be partitioned out of the primary variables of interest. Our hypotheses deal specifically with the interaction of main effect variables with time; however, we need to control for the conditional main effect (i.e., the lower ordered effect) of these variables as well. Thus, the conditional main effects for strategic orientation (FP/NFP; teaching/non-teaching), formal structure (hospital size, system size), and internal dynamics (CMI) of the hospital are all control variables.

In addition to the control variables listed above, we also draw from literature on another enterprise-wide information system—in particular, ERP systems—to identify other covariates. ERP system research has found that cross-module integration is a significant concern for organizations (Bingi et al. 1999; Kumar et al. 2003). To the extent that older hos-

[3]Hospitals can change from FP to NFP or from teaching to non-teaching in a given year, which is accounted for in our analysis.

Table 3. Descriptive Data

Year	Statistic	Closeness† to Single-Sourcing	Hospital Age (years)	For-Profit	Teaching	Hospital Size (staffed beds)	Size Health System	Case Mix Index
2005	Median/[Total]	1.000	12	[1073]	[308]	150	6	1.31
	Mean	0.826	30.7	0.32	0.09	195.6	32.5	1.36
	Std. Dev.	0.264	34.9	0.47	0.29	169.5	56.6	0.26
2006	Median/[Total]	1.000	13	[1073]	[305]	150	5	1.32
	Mean	0.848	31.7	0.32	0.09	195.6	21.9	1.37
	Std. Dev.	0.258	34.9	0.47	0.29	171.2	39.7	0.26
2007	Median/[Total]	1.000	14	[1073]	[295]	150	5	1.34
	Mean	0.868	32.7	0.32	0.09	194.7	24.2	1.39
	Std. Dev.	0.251	34.9	0.47	0.28	170.7	43.3	0.25
2008	Median/[Total]	1.000	15	[1073]	[287]	150	5	1.36
	Mean	0.874	33.5	0.32	0.08	195.3	23.1	1.40
	Std. Dev.	0.246	36.0	0.47	0.28	172.1	40.8	0.26
2009	Median/[Total]	1.000	16	[1073]	[286]	150	5	1.39
	Mean	0.888	34.2	0.32	0.08	195.1	23.3	1.41
	Std. Dev.	0.237	34.6	0.47	0.28	172.6	40.8	0.26
2010	Median/[Total]	1.000	17	[1073]	[254]	150	5	1.43
	Mean	0.889	35.2	0.32	0.07	195.8	22.9	1.44
	Std. Dev.	0.237	37.1	0.47	0.26	173.7	39.6	0.26
2011	Median/[Total]	1.000	18	[1073]	[214]	150	5	1.46
	Mean	0.885	36.0	0.32	0.06	195.6	23.6	1.47
	Std. Dev.	0.229	35.0	0.47	0.24	174.5	39.7	0.27
2012	Median/[Total]	1.000	19	[1073]	[203]	150	6	1.47
	Mean	0.892	37.4	0.32	0.06	195.7	25.5	1.49
	Std. Dev.	0.239	34.4	0.47	0.24	176.3	41.8	0.27
2013	Median/[Total]	1.000	20	[1073]	[204]	149	7	1.48
	Mean	0.887	38.7	0.32	0.06	195.5	27.8	1.49
	Std. Dev.	0.230	34.8	0.47	0.24	177.4	43.7	0.26

† We report the *adjusted* closeness ranging from 0 to 1 on a continuum, with higher values indicating greater similarity to a prototypical single-sourcing strategy. The *unadjusted* closeness, which divides by 5 or the total number of modules in a complete EMRS suite, irrespective of the number adopted, is reported in the appendix.

pitals have a higher percentage of legacy IT systems in use (Schneider 2013), we would expect them to be less likely to abandon individual modules that are well-understood and accepted by clinicians. The consequence of this is that older hospitals will be encumbered by existing systems (Lamb 2008), and thus more apt to adopt individual (i.e., best of breed) modules that may or may not integrate cleanly with the other modules. In addition, the maturity of the firm is a powerful formal structure that has been shown to dictate actions (Stinchcombe 1965; Tolbert and Zucker 1983).

There is no known theoretical reason to believe that the effect age has on sourcing strategy will remain constant over time. In fact, the opposite is likely to be true because data accumulates over time and younger hospitals will face less burdensome data transformation processes if or when they move to an entirely new EMRS suite. In addition, because they were founded later, younger hospitals will have fewer legacy systems and thus may be more willing to adopt a new sourcing strategy. Consequently, theory would predict that more established hospitals are locked-in to specific modules and less willing to evolve with the conditions in their environments (Johnson 2007; Kelly and Amburgey 1991; Sydow et al. 2009). Therefore, we control for age and time (year since 2005) individually, as well as control for their interaction.

Analysis and Results

We used mixed effects models (also termed multilevel or hierarchical linear) to model the closeness to single-sourcing as a linear function of year, the control variables, and the interaction of the five antecedents with year in a mixed effects longitudinal modeling framework (Singer and Willett 2003). For purposes of interpretation, we use "year since 2005," thus making 2005 the baseline year of 0; 2006 year 1; 2007 year 2; etc. The mixed effects model was used because the outcome variable is repeatedly measured within each hospital, and thus the measures over time are nested within the hospital. We modeled fixed effects for the effect of the above noted variables and the intercept and linear change (slope) as well as random effects for the intercept and slope of each hospital over time. That is, each hospital was allowed its own intercept and its own slope. Additionally, we allowed the random intercept and slope to correlate.[4] We used restricted information maximum likelihood, with implementation of the model being done using R (R Case Team 2016) with the lme4 package (Bates et al. 2014).

Before discussing our results, we first address potential endogeneity concerns, which could be a threat to the causal implications of our model. First, as noted above, institutional theorists have argued that institutions are powerful, long-lasting structures that are embedded within firms (Stinchcombe 1965; Tolbert and Zucker 1983). Even variables such as FP/NFP and teaching/non-teaching are not endogenous choices that managers are currently making, but instead are typically historical features that describe the hospital. Thus, we argue that all of the antecedents we use are exogenous, and others have treated them as such in the EMRS context (Angst et al. 2010; Angst et al. 2017; Peng et al. 2014). Furthermore, case mix index is not determined by the hospital. Patient characteristics are exogenous to the hospital and are instead a function of the patient population (Pettengill and Vertrees 1982). Finally, from an empirical standpoint, we included a random intercept and slope for each hospital (and allowed them to correlate) to account for otherwise unobserved invariant heterogeneity, thereby reducing concerns of omitted variable biases.

We used a model building approach in a taxonomy of increasingly more complicated (richer) models, which are given in Table 4. To begin, we fit a means-only model, in which each hospital has its own intercept but no slope (i.e., no effect of time). We do this to estimate the intraclass correlation coefficient, which is the "population estimate of the variance explained by the grouping structure" (Hox 1995, p. 14); in our case, this is the overall variability that is explained by hospital. The value of the intraclass correlation coefficient here is 0.62—meaning that about 62% of the variance in the closeness to single-sourcing is accounted for by the hospital alone. We take as our primary model of interest the one presented in column 6, which includes all of the control variables and the interaction of each predictor with time. Model 6 fits statistically better than the model without the interaction terms (i.e., see 6 versus 5 Model Comparison, Table 4).

We do not find a statistically significant interaction between time and FP hospitals (β_{FP} = -0.001, $p > 0.10$), which means that we do not have evidence they are moving more quickly toward single-sourcing than NFP hospitals, thus H1 is not supported. Our finding relative to teaching hospitals (H2) is opposite of what was hypothesized, but very interesting. The interaction between time and teaching hospital is positive and statistically significant (β_{Teach} = 0.009, $p < 0.01$), meaning that over the time period examined, teaching hospitals move toward single-sourcing more quickly (i.e., the effect that being a teaching hospital has on closeness to single-sourcing is increasing over time) than do non-teaching hospitals. In terms of effect size (e.g., Kelley and Preacher 2012), in the year 2005, holding other values at their median, a hospital that is one standard deviation above the mean hospital age (mean and standard deviation in 2005 are 30.7 and 34.9 years, respectively) has a predicted outcome (closeness to single-sourcing) of 0.823, while a hospital one standard deviation below the mean has a predicted value of 0.865, yielding a difference of 0.042 units. It is important to note, however, that the effect of these variables is not constant across the time period under investigation.[5] Similarly, H3 is supported in that larger hospitals move toward single-sourcing more quickly than smaller hospitals (β_{StfBed} = 0.006, $p < 0.001$). The size of the health system has a statistically significant negative interaction with time, which is counter to our expected effect in H4 ($\beta_{SysSize}$ = -0.0012, $p < 0.01$). Our last result tests the effect of case complexity on sourcing strategy (H5). The CMI–time interaction is in the posited direction (β_{CMI} = -0.006, $p < 0.05$), supporting our hypothesis. To help interpret these findings associated with interaction terms, we provide visualizations in Figure 4 of the change trajectories for each of the predictors (in separate panels). For the top-left panel, we plot the trajectories for FP versus NFP for non-

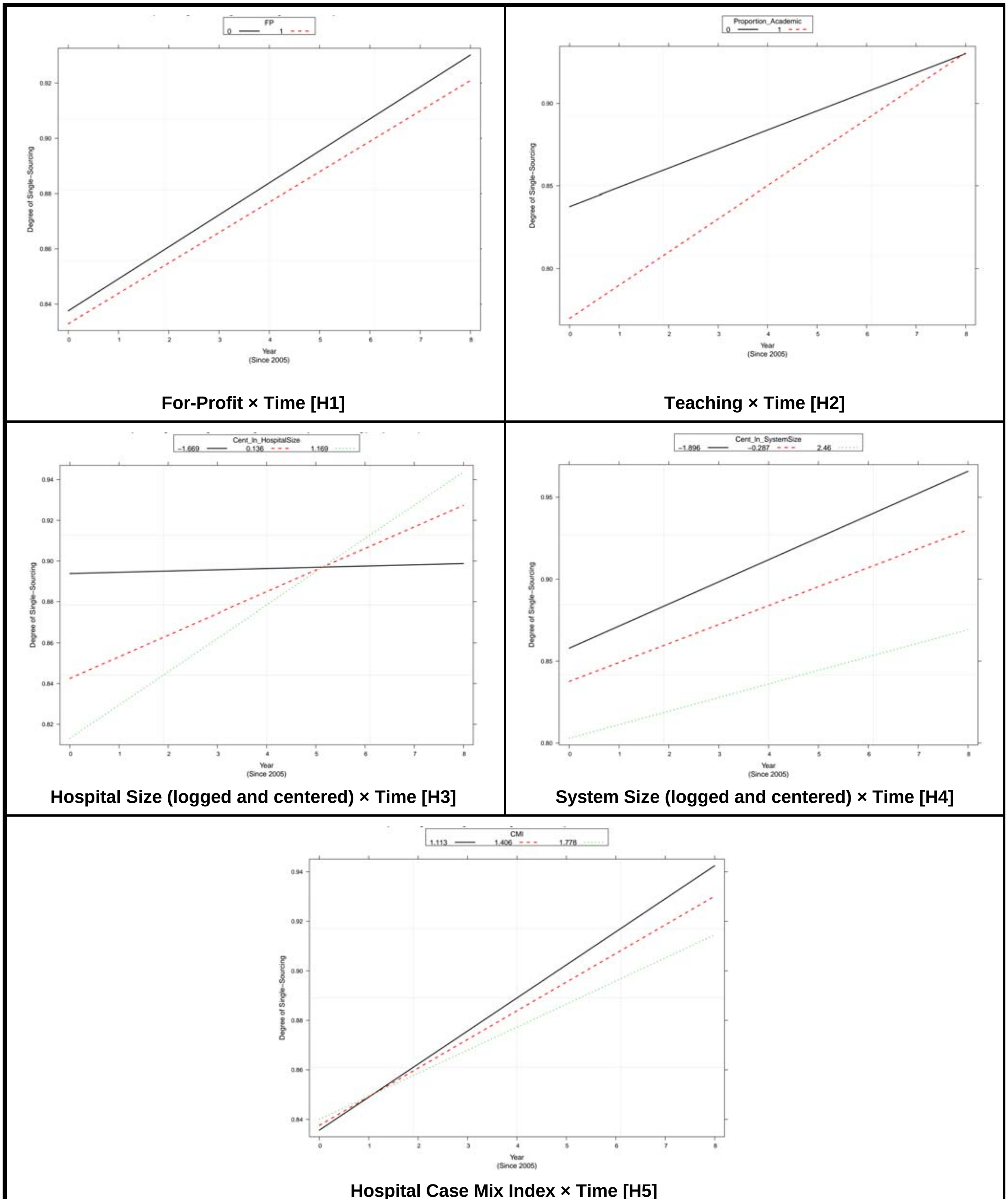
[4]It is important to note that hospitals that employed a prototypical single-sourcing strategy as a starting point (i.e., in the first year of our sample) or across all 9 years were not eliminated from our analysis. Specifically, we hypothesize about the rate of change (i.e., how much a variable increases or decreases toward closeness to single-sourcing over time) and thus assess this rate of change by interacting our focal independent variable with time. Consequently, if a hospital uses a prototypical single-sourcing strategy, it would simply have a flatter slope in our analysis than hospitals that are employing a prototypical multisourcing strategy.

[5]We provided this discussion of effect size as an example only and do not discuss the other variables due to space restrictions. The interpretation of the effect size is complicated by the fact that our variables of interest are interacted with time, therefore we must talk in terms of unit changes in discrete years or changes in slope over time, both of which require extensive elaboration. We chose the age variable because it was statistically significant and it was a continuous variable, as opposed to dichotomous, thus a deviation is meaningful.

Table 4. Mixed Effects Regression Results for Closeness to Single-Sourcing

		Model Number and Description					
	Parameter	**1 Intercept Only**	**2 + Slope**	**3 + Strategic Orientation**	**4 + Formal Structure**	**5 + Internal Dynamics**	**6 + Interactions**
	Intercept	0.869*** (0.003)	0.831*** (0.005)	0.854*** (0.005)	0.846*** (0.005)	0.871*** (0.016)	0.840*** (0.025)
Control Variables	Slope (YearSince2005)		0.009*** (0.001)	0.009*** (0.001)	0.009*** (0.001)	0.010*** (0.001)	0.017*** (0.004)
Control Variables	For-Profit (FP)			-0.057*** (0.007)	-0.036*** (0.007)	-0.009 (0.007)	-0.005 (0.010)
Control Variables	Teaching (Teach)			-0.021 (0.014)	-0.034* (0.014)	-0.022† (0.013)	-0.068*** (0.019)
Control Variables	Hospital Size (ln_StfBed)				-0.003 (0.003)	-0.005 (0.004)	-0.028*** (0.006)
Control Variables	System Size (ln_SysSize)				-0.021*** (0.001)	-0.017*** (0.002)	-0.013*** (0.002)
Control Variables	Hospital Age (lnAge)				0.007† (0.004)	0.010* (0.004)	0.025*** (0.006)
Control Variables	Case Complexity (CMI)					0.020† (0.011)	0.007 (0.018)
Control Variables	lnAge × YearSince2005						-0.003*** (0.0009)
Interactions of Interest	FP × YearSince2005						-0.001 (0.002)
Interactions of Interest	Teach × YearSince2005						0.009** (0.003)
Interactions of Interest	ln_StfBed × YearSince2005						0.006*** (0.001)
Interactions of Interest	ln_SysSize × YearSince2005						-0.0012** (0.0004)
Interactions of Interest	CMI × YearSince2005						-0.006* (0.003)
	Pseudo-R^2	.668	.817	.813	.814	.7869	.7874
	Model Comparison		2 vs. 1 $\chi^2(3) = 12410$***				6 vs. 5 $\chi^2(6) = 168$***
	n-Hospitals	3,417	3,417	3,322	3,318	2,824	2,824
	n-Observations	29,033	29,033	28,241	28,210	22,809	22,809
	LL	-894	5305	5854	5926	5126	5126

† $p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$



For-Profit × Time [H1]

Teaching × Time [H2]

Hospital Size (logged and centered) × Time [H3]

System Size (logged and centered) × Time [H4]

Hospital Case Mix Index × Time [H5]

Figure 4. Graphs of Interactions: Closeness to Single-Sourcing

teaching hospitals with all continuous predictors held at their median. For the top-right panel we plot teaching versus non-teaching hospitals for FP hospitals, holding continuous predictors at their median. For the remaining plots we use FP hospitals that are non-teaching hospitals and use the 10th, 50th, and 90th percentiles as selected values to plot (these are the values given in the legend of each plot).

In our primary analysis, we used an *adjusted* closeness to single-sourcing variable, which divides the *adist* output by the number of modules actually adopted in the EMRS suite (ranges from 2 to 5). In the appendix, as a robustness check, we report additional results where the *adist* output is always divided by 5, which is the maximum number of modules in a complete EMRS suite. We call this the *unadjusted* closeness to single-source variable (see the examples in the appendix as well as Tables A1 and A2 for comparisons between the two measures and descriptive statistics). The results of our hypothesized effects remain mostly consistent (see Table A3). All hypothesized interactions between the organizational antecedents and time are directionally the same irrespective of the closeness to single-sourcing variable used. The interaction of FP with time becomes statistically significant ($p < 0.001$) while the interaction of teaching hospital with time slips to being marginally nonsignificant ($p = 0.13$). Theory and prior research comparing sequences such as the type we investigate has not established which measure is appropriate and thus we report both.

Discussion

Our longitudinal analysis offers several important insights about the dynamic EMRS sourcing strategies pursued by U.S. hospitals. First, our results clearly suggest that hospitals are migrating toward a single-sourcing strategy for their EMRS as evident by the coefficient on slope, which is positive and significant in all models ($\beta_{YearSince2005}$ ranges between 0.009 and 0.017, $p < 0.001$). Lured by the expectation of more seamless integration across modules and lower transaction costs, hospitals are increasingly consolidating their spending and forging more meaningful relationships with fewer suppliers. This finding is intriguing in light of the extant research suggesting that multisourcing arrangements are becoming more common in sourcing IT services at large (Bapna et al. 2010; Lacity et al. 2009; Lacity and Willcocks 1998; Levina and Su 2008). Conversely, this move toward single-sourcing parallels the trend in many manufacturing sectors toward a smaller, rationalized supply base. While the overarching trend is toward hospitals single-sourcing their EMRS, our findings demonstrate that different types of hospitals are progressing toward single-sourcing at different rates. That is, some types of hospitals are adapting more quickly to a single-sourcing model.

Before discussing the results associated with our hypothesized antecedents, it is insightful to briefly comment on the negative association between hospital age and time (i.e., $\beta_{lnAge \times YearSince2005} = -0.003$, $p < 0.001$) and migration toward single-sourcing. As expected, older hospitals are more likely to be saddled with complex networks of legacy IT systems, which would indicate slower movement toward single-sourcing. The effect of time as it relates to hospital age is also very important, since the main effect and conditional main effects of hospital age are actually positive in the absence of the time effect (see Table 4, $\beta_{lnAge} = 0.007$ and 0.025, respectively).

Grounded in institutional theory, we analyzed a theoretical model of the degree to which five salient hospital characteristics determine the rate at which hospitals migrate toward single-sourcing. The results for two of these antecedents supported our hypotheses. First, our results reveal that larger hospitals migrate toward single-sourcing more quickly than smaller hospitals. This is consistent with our expectation that larger hospitals have more slack resources, and therefore capacity to enact change, as well as have a greater ability to withstand the potentially disruptive nature of a rapid migration toward single-sourcing. Second, the results also support our hypothesis that hospitals with a higher case mix index will be slower to adopt a single-sourcing strategy, yet this effect does not exist in the earlier years as evident by the positive and significant conditional main effect (see the last interaction plot in Figure 4). While hospitals that handle a more complex mix of patient cases are more likely to choose technologies that align with their innovative clinical practices (i.e., desire multisourcing), in the earlier years of our sample, lower complexity hospitals employed more of a multisourcing strategy. One possible explanation for this is that EMRS technology was less mature in the earlier years in that no single supplier was producing top quality products for all five modules; thus low complexity hospitals (because they were less hindered by complex cases) had the opportunity to experiment with multiple suppliers. Through this experimentation process, it is possible that the low complexity hospitals learned and purposefully migrated toward single-sourcing. At the same time, hospitals with more complex cases are more likely to seek out the best technologies that match their current clinical and patient care processes, which favors a multisourcing strategy.

Although the results associated with hospital size and case mix index were supportive of our hypotheses, the findings regarding FP hospitals, teaching hospitals, and health system size did not support our expectations. Arguing that FP hospitals would have more slack resources than NFP hospitals, we anticipated that FP hospitals would move more quickly toward single-sourcing. However, we found there was no statistical difference between the two strategic orientations.

Counter to our hypothesis, our mixed effects regression results also indicate that teaching hospitals are migrating toward single-sourcing faster than non-teaching hospitals. Yet, a complete understanding of the relationship between hospital teaching status and the trend toward single-sourcing requires careful evaluation of Figure 4, which offers additional insight as to the nature of this relationship. Specifically, Figure 4 shows that non-teaching hospitals start out much closer to single-sourcing in the early years, but teaching hospitals are migrating much faster, to the point of catching up with non-teaching hospitals in recent years. Therefore, the quicker migration of teaching hospitals toward single-sourcing is explained, at least in part, by the fact that non-teaching hospitals, on average, were already operating much closer to single-sourcing from the outset of our study's time frame.

We theorized that the research mission and medical training focus of teaching hospitals would motivate them to stick with best-of-breed software applications that more closely aligned with their desired clinical practices, regardless of the specific technology supplier. The observation that non-teaching hospitals were closer to single-sourcing (relative to teaching hospitals) at the beginning of our study's time frame is consistent with this theoretical expectation. However, the finding that teaching hospitals are catching up in later years by migrating more quickly toward single-sourcing is consistent with teaching hospitals increasingly viewing single-sourcing as a cutting-edge strategy. As with all technologies, there are likely to be considerable differences in the functionality of individual EMRS modules in the early years of adoption, which would seem to favor a best-of-breed (multisourcing) strategy. Therefore, we would expect that teaching hospitals would maintain specific modules that suited doctor preferences, and the data support this. However, in later years the functionality challenges are likely to diminish, and it is probable that seamless integration becomes the driving factor for sourcing decisions. In simple terms, the benefits associated with multisourcing best-of-breed modules diminishes and the interoperability associated with single-sourcing becomes the key driver of adoption. This would seem to support the findings of Ford et al. (2010). While Ford et al. focused on intended strategy (i.e., the data they used simply asked respondents what sourcing strategy they intended to migrate toward), they found that teaching hospitals are more likely to have fully implemented EMRS than non-teaching hospitals, and that more fully implemented EMRS are often closer to single-sourcing. The use of a single supplier generally relates to more seamlessly integrated EMRS modules, which mitigates the need for redundant, error-prone data entry and allows clinical staff to focus more on providing patient care and training the next generation of healthcare practitioners. This, on further reflection, seems to support teaching hospitals migrating toward single-sourcing more quickly.

Finally, we posited that hospitals that are part of larger health systems would be pressured to adopt standard technologies allowing the system to leverage its purchasing clout and achieve economies of scale with training and support staff. This suggests that hospitals that are members of larger systems would move more quickly toward single-sourcing. However, our results again indicate that the opposite is occurring. Plausibly, moving to an EMRS provided by a single supplier may be more difficult and costly in larger systems than in smaller systems or a stand-alone hospital. Attempting to standardize across the system may involve the establishment of a cross-hospital sourcing committee and consensus around the supplier selected. As such, it is likely far easier to make one-off module-level sourcing decisions than it is to agree upon a single supplier for all modules in the EMRS. Thus, even if larger systems intend to adopt a single-sourcing strategy, bringing this to fruition may simply be a slower, more time-consuming endeavor than for smaller health systems.

Viewing our findings as a whole, it is interesting that larger hospitals migrate toward single-sourcing more quickly than smaller hospitals, but hospitals in larger systems migrate toward single-sourcing more slowly than hospitals in smaller systems. A possible explanation for the latter, more counterintuitive finding is that a second mechanism is at play with large health systems. Specifically, the phenomenon of multi-hospital systems is relatively new and only in the last two decades have massive systems (100+ hospitals) come into existence (Melnick and Fonkych 2016). While the intent of these mergers and acquisitions is to find efficiencies through scale and scope (Boulton 2015), our data suggests this "buying spree"[6] has resulted in scores of different sourcing strategies and little consistency across hospitals within the same system.[7] Consequently, it may be only a matter of time

[6]In 2014, there were 102 mergers and acquisitions among health systems, versus 59 in 2004 and 50 in 2005 (Boulton 2015).

[7]We conducted a *post hoc* analysis using 2013 data (the most recent year of our data) and calculated the Herfindahl-Hirschman Index (HHI) (Herfindahl 1950)—a measure of market concentration—for each health system using the number of different EMRS suppliers as our measure of concentration. While one very large health system (over 100 hospitals) successfully deployed a single supplier for all adopted EMRS modules across all of its hospitals (i.e., HHI = 10,000), this phenomenon is not common—it occurs only three times in systems with 38 or more hospitals. In most cases, there is wide variation in both small and large health systems. The mean and standard deviation of HHI in systems with more than 20 hospitals is 6,466 and 2,886.9, respectively, where an HHI of 10,000 represents one supplier across all modules in

before large health systems mandate that certain EMRS suppliers be used. In fact, some have speculated that larger health systems will disproportionately benefit from the implementation of system-wide EMRS because they will be able to analyze greater quantities of data in an attempt to reduce costs and gain efficiencies (Boulton 2015). In the shorter term, however, it is apparent from our findings that if a system-wide directive toward single-sourcing is imposed, it is not yet translating into action at the hospital level. A thorough examination of these possibilities is beyond the scope of the current study, but is certainly worthy of future investigation. Over the time frame of our study, the desire for, or momentum from "institutional heterogeneity" within health systems appears to outweigh the leverage and economies of scale arguments we provided.

In short, while institutional theory effectively predicted some relationships, it failed in other cases. One overarching explanation for this lack of consistency, offered by Hannan and Freeman (1984), is that some organizational features are more central (core) to an organization's identity than others (peripheral). It could be that formal structure, for example, dampens the effect of strategic orientation, or vice versa. This is an important area for future research.

Theoretical Contributions

This study makes three important scholarly contributions. First, our findings demonstrate that sourcing strategies are context-specific. We were able to identify several factors that significantly influence the sourcing strategy pursued and the speed with which it is pursued. In doing so, we shed light on key organizational-level characteristics that influence a hospital's single-sourcing versus multisourcing approach to EMRS. Second, our longitudinal data afford us the opportunity to capture how sourcing decisions unfold into a *strategy* over time. Taking a dynamic perspective allowed us to evaluate how hospitals differ in their sourcing trajectories, offering richer insights into the actual strategies being pursued than could be discovered using a cross-sectional analysis. Indeed, our results demonstrate that looking at a hospital's sourcing approach within any single year provides an incomplete, and perhaps inaccurate, picture as to their realized strategy, which can only be captured after multiple reinforcing decisions. Given that insights from the manufacturing sourcing literature may not transfer cleanly to the context of sourcing modular IT systems, these findings contribute much needed empirical evidence to the sparse IT sourcing strategy literature. Finally, we present a novel sequence analysis approach to quantifying sourcing configurations. To our knowledge, ours is the first study to employ sequence analysis to quantitatively characterize sourcing configurations. Specifically, we demonstrate how distance measures based on sequence analysis can be used to assess the degree to which an observed sourcing configuration deviates from a prototypical single-sourcing approach. We also identify a means of coding the sequences that allows for comparisons across different suppliers. While this approach is not truly a *theoretical* contribution in and of itself, it certainly represents an important empirical advancement and a methodological contribution for which future sourcing studies can derive valuable insights.

Managerial Contributions

Beyond the theoretical contributions outlined above, our study has important managerial implications. Although there is a general trend toward single-sourcing EMRS, our study sheds light on which hospital characteristics lead to quicker migration toward single-sourcing and, because we anchored multisourcing at the opposite end of the continuum, it also provides insight on which characteristics lead to multisourcing. These findings are managerially important for multiple reasons. First, our findings allow hospitals to assess the sourcing strategies employed by their peers and follow suit, if desired. Specifically, our research allows hospitals to contrast their own approach to sourcing EMRS with these benchmarks to evaluate their consistency with these trends in the industry at large. In the case of a deviation from these overarching trends, managers might wish to reevaluate their current strategy to determine its appropriateness. In some cases, hospitals might not have clearly articulated a deliberate EMRS sourcing strategy, in which case they are following more of an *ad hoc* sourcing approach, which is likely less optimal. In this situation, the insights from this study provide valuable benchmarking information for hospitals, and can serve as an important input to the strategy development process. Second, some hospitals may have a traditional orientation toward a particular sourcing configuration (i.e., a tradition of using a single-sourcing or multisourcing configuration). If the hospital desires to transform its strategy to better align with peer group norms, it may require a considerable effort to overcome organizational inertia. The insights developed by this study can aid health IT sourcing professionals in convincing various groups to buy-in to an alternative sourcing configuration. This buy-in can in turn improve the chances of implementation success. Additionally, while things like age are certainly immutable, it is in the best interest of managers to understand what it is about the imprint left by age that

all hospitals and numbers approaching 0 represent high variation in suppliers used. In short, while there is a trend toward single-sourcing, it appears to take time for health systems to get all of their hospitals to move in that direction, if that is their intent.

makes an organization more or less resistant to changes in IS sourcing strategies. For example, older hospitals could more vigorously pursue tactics for injecting new sourcing ideas into the organization. Third, our research sheds light on tradeoffs involved in sourcing decisions at the organizational level. For example, implementing a multisourcing strategy may offer local optimization (i.e., individual units select the best technology for their needs), but hinder global optimization due to interdepartmental interoperability issues. Vice versa, single-sourcing may offer global optimization due to improved interdepartmental interoperability, but limited local optimization due to the need to reengineer business processes. Finally, our findings are important for policy as well. Since 2004, the Office of the National Coordinator for Health Information Technology (ONCHIT) has been instrumental in coordinating nationwide efforts to advance the use of health IT (ONC 2016). In that capacity, the office has guided standards development and piloted technology rollouts in hospitals across the country. Our research could be used to recruit specific types of hospitals that are trending toward one sourcing strategy. Specifically, our study sheds light on the rate at which hospitals are moving toward single-sourcing, and thus specific hospitals could be chosen based on their stage of migration.

Conclusion

Using a rich longitudinal dataset, this study provides a dynamic view of the EMRS sourcing strategies pursued in U.S. hospitals, and identifies key organizational-level antecedents driving the observed trends in practice. The methods employed and insights derived have important implications for both research and practice. Notwithstanding these contributions, the limitations of this study present multiple opportunities for future research. First, this study only considers a single element of the overall sourcing strategy: the configuration of suppliers used. While this is a particularly salient aspect of a sourcing strategy (Elmaghraby 2000), future scholars are encouraged to explore other elements of an overall sourcing strategy. For example, examining factors driving a hospital's supplier switching behavior would be particularly interesting and could leverage the longitudinal nature of available data. Another important aspect to study is the potential influence that powerful EMRS suppliers have. As the EMRS market begins to consolidate, it is likely that some suppliers will mandate that their modules be bundled in an all-or-none fashion, or they will offer significant pricing discounts when multiple modules are bundled. But we do not have sufficiently detailed information about supplier pricing strategies to ascertain the extent to which this is happening. We do know that significant variation exists in the number of suppliers used, as represented in our data, suggesting that bundling is not widely used during the time frame under investigation, but it is feasible that it will emerge in the future.

A second limitation is that our analysis relied on organizational-level antecedents of sourcing strategies for which data are publicly accessible. Certainly, this stream of research could benefit from analyzing the role of other sourcing strategy antecedents such as government mandates and/or incentives, buy-in from clinical staff, buyer–supplier relationships, and others that may require primary data collected through surveys or field interviews. Third, future scholars can examine the strength of various hospital characteristics that drive sourcing decisions. We find that teaching and larger hospitals migrate toward single-sourcing more quickly, but older hospitals migrate more slowly. Little is known, however, about how quickly larger, older teaching hospitals migrate toward single-sourcing. In other words, how do these individual hospital characteristics interact with one another in their impact on sourcing strategy?

We leverage institutional theory, which argues that hospitals are motivated to follow the strategies exhibited by their peers, but future scholars may wish to draw upon a different theoretical lens, which could lead to unique insights. For example, upper echelons theory argues that an organization's strategy has little or nothing to do with the practices and/or strategies exhibited by its peers, but instead reflects the values, experiences, and beliefs of the organization's top executives (Hambrick and Mason 1984). Perhaps teaching hospitals and larger hospitals attract top executives who are more similar in regard to their values, experiences, and beliefs than top executives at other hospitals (e.g., FP or older), which could be why these hospitals appear to implement the same sourcing strategy more quickly than other hospitals. Similarly, we examine a hospital's realized (rather than intended) sourcing strategy (Mintzberg 1978), but an interesting future research direction could be to examine the degree to which a hospital's realized and intended sourcing strategies diverge. Does a hospital's realized sourcing configuration in each year eventually converge with its intended long-term sourcing strategy or are the two often misaligned? Furthermore, are there negative performance implications associated with having a discrepancy between a hospital's realized and intended sourcing strategies? Finally, the dependent variable in this study is the sourcing strategy pursued. A natural extension to the present work would be to relate the chosen sourcing strategy, or the degree of alignment with a best practice strategy, to some indicator of performance. In sum, the current study opens the door to several interesting avenues for future scholarly work.

References

Abbott, A. 1983. "Sequences of Social Events," *Historical Methods* (16:4), pp. 129-147.

Abbott, A., and Forrest, J. 1986. "Optimal Matching Method for Historical Sequences," *Journal of Interdisciplinary History* (16:3), pp. 471-494.

Abbott, A., and Hrycak, A. 1990. "Measuring Resemblance in Sequence Data: An Optimal Matching Analysis of Musicians' Careers," *American Journal of Sociology* (96:1), pp. 144-185.

Adler-Milstein, J., Everson, J., and Lee, S.-Y. D. 2014. "Sequencing of EHR Adoption among US Hospitals and the Impact of Meaningful Use," *Journal of the American Medical Informatics Association* (21:6), pp. 984-991.

Agarwal, R., Gao, G., DesRoches, C., and Jha, A. K. 2010. "Research Commentary—The Digital Transformation of Healthcare: Current Status and the Road Ahead," *Information Systems Research* (21:4), pp. 796-809.

Agha, L. 2014. "The Effects of Health Information Technology on the Costs and Quality of Medical Care," *Journal of Health Economics* (34:March), pp. 19-30.

Ahmadjian, C. L., and Robinson, P. 2001. "Safety in Numbers: Downsizing and the Deinstitutionalization of Permanent Employment in Japan," *Administrative Science Quarterly* (46:4), pp. 622-654.

Ang, S., and Cummings, L. L. 1997. "Strategic Response to Institutional Influences on Information Systems Outsourcing," *Organization Science* (8:3), pp. 235-256.

Angst, C. M., Agarwal, R., Sambamurthy, V., and Kelley, K. 2010. "Social Contagion and Information Technology Diffusion: The Adoption of Electronic Medical Records in U.S. Hospitals," *Management Science* (56:8), pp. 1219-1241.

Angst, C. M., Block, E. S., D'Arcy, J., and Kelley, K. 2017. "When Do IT Security Investments Matter? Accounting for the Influence of Institutional Factors in the Context of Healthcare Data Breaches," *MIS Quarterly* (41:3), pp. 893-916.

Angst, C. M., Devaraj, S., Queenan, C., and Greenwood, B. 2011. "Performance Effects Related to the Sequence of Integration of Healthcare Technologies," *Production and Operations Management* (20:3), pp. 319-333.

Bapna, R., Barua, A., Mani, D., and Mehra, A. 2010. "Research Commentary—Cooperation, Coordination, and Governance in Multisourcing: An Agenda for Analytical and Empirical Research," *Information Systems Research* (21:4), pp. 785-795.

Bates, D., Maechler, M., Bolker, B., and Walker, S. 2014. "lme4: Linear Mixed-Effects Models Using 'Eigen' and S4," R Package Version 1.0–6 (https://cran.r-project.org/web/packages/lme4/index.html).

Baum, J. A. C., and Oliver, C. 1991. "Institutional Linkages and Organizational Mortality," *Administrative Science Quarterly* (36:2), pp. 187-218.

Becker, A. L. 2014. "How Different Are For-Profit and Nonprofit Hospitals?," *Connecticut Network*, April 25 (https://ctmirror.org/2014/04/25/how-different-are-for-profit-and-nonprofit-hospitals/).

Berger, P. D., Gerstenfeld, A., and Zeng, A. Z. 2004. "How Many Suppliers Are Best? A Decision-Analysis Approach," *Omega* (32:1), pp. 9-15.

Bingi, P., Sharma, M. K., and Godla, J. K. 1999. "Critical Issues Affecting an ERP Implementation," *IS Management* (16:3), pp. 7-14.

Boulton, G. 2015. "Wave of Consolidation Engulfing Health Care Systems," *Journal Sentinel* (http://archive.jsonline.com/business/wave-of-consolidation-engulfing-health-care-systems-b99474527z1-298731631.html).

Boxenbaum, E., and Jonsson, S. 2008. "Isomorphism, Diffusion, and Decoupling," in *The Sage Handbook of Organizational Institutionalism,* R. Greenwood, C. Oliver, K. Sahlin, and R. Suddaby (eds.), London: Sage, pp. 299-323.

Bozarth, C., Handfield, R., and Das, A. 1998. "Stages of Global Sourcing Strategy Evolution: An exploratory study," *Journal of Operations Management* (16:2), pp. 241-255.

Brailer, D. J. 2005. "Interoperability: The Key to the Future Health Care System," *Health Affairs* (24:January 10), pp. W5-19-W15-21.

Buntin, M. B., Burke, M. F., Hoaglin, M. C., and Blumenthal, D. 2011. "The Benefits of Health Information Technology: A Review of the Recent Literature Shows Predominantly Positive Results," *Health Affairs* (30:3), pp. 464-471.

Burke, G. J., Carrillo, J. E., and Vakharia, A. J. 2007. "Single Versus Multiple Supplier Sourcing Strategies," *European Journal of Operational Research* (182:1), pp. 95-112.

Chaudhry, B., Wang, J., Wu, S., Maglione, M., Mojica, W., Roth, E., Morton, S. C., and Shekelle, P. G. 2006. "Systematic Review: Impact of Health Information Technology on Quality, Efficiency, and Costs of Medical Care," *Annals of Internal Medicine* (144:10), pp. E12-E22.

Classen, D. C., and Bates, D. W. 2011. "Finding the Meaning in Meaningful Use," *New England Journal of Medicine* (365:9), pp. 855-858.

Costantino, N., and Pellegrino, R. 2010. "Choosing Between Single and Multiple Sourcing Based on Supplier Default Risk: A Real Options Approach," *Journal of Purchasing and Supply Management* (16:1), pp. 27-40.

D'Aunno, T., Sutton, R. I., and Price, R. H. 1991. "Isomorphism and External Support in Conflicting Institutional Environments: A Study of Drug Abuse Treatment Units," *Academy of Management Journal* (34:3), pp. 636-661.

Dacin, M. T., Goodstein, J., and Scott, W. R. 2002. "Institutional Theory and Institutional Change: Introduction to the Special Research Forum," *Academy of Management Journal* (45:1), pp. 45-56.

Damanpour, F. 1992. "Organizational Size and Innovation," *Organization Studies* (13:3), pp. 375-402.

Damanpour, F. 1996. "Organizational Complexity and Innovation: Developing and Testing Multiple Contingency Models," *Management Science* (42:5), pp. 693-716.

Deeter, B. 2013. "Best of Breed Applications Finally Have Their Day," *The Wall Street Journal*, February 14 (http://blogs.wsj.com/cio/2013/02/14/best-of-breed-applications-finally-have-their-day/).

Deming, W. E. 1986. *Out of the Crisis*, Cambridge, MA: MIT Press.

DiMaggio, P., and Powell, W. 1983. "The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields," *American Sociological Review* (48:2), pp. 147-160.

Dobrev, S. D., Kim, T. Y., and Carroll, G. R. 2003. "Shifting Gears, Shifting Niches: Organizational Inertia and Change in the Evolution of the U.S. Automobile Industry, 1885-1981," *Organization Science* (14:3), pp. 264-282.

Dyer, J. H. 1997. "Effective Interfirm Collaboration: How Firms Minimize Transaction Costs and Maximize Transaction Value," *Strategic Management Journal* (18:7), pp. 535-556.

Ehie, I. C., and Madsen, M. 2005. "Identifying Critical Issues in Enterprise Resource Planning (ERP) Implementation," *Computers in Industry* (56:6), pp. 545-557.

Elmaghraby, W. J. 2000. "Supply Contract Competition and Sourcing Policies," *Manufacturing & Service Operations Management* (2:4), pp. 350-371.

Fetter, R. B., Shin, Y., Freeman, J. L., Averill, R. F., and Thompson, J. D. 1980. "Case Mix Definition by Diagnosis-Related Groups," *Medical Care* (18:2), pp. 1-53.

Ford, E. W., Huerta, T. R., Menachemi, N., Thompson, M. A., and Yu, F. 2013. "Health Information Technology Vendor Selection Strategies and Total Factor Productivity," *Health Care Management Review* (38:3), pp. 177-187.

Ford, E. W., Menachemi, N., Huerta, T. R., and Yu, F. 2010. "Hospital IT Adoption Strategies Associated with Implementation Success: Implications for Achieving Meaningful Use," *Journal of Healthcare Management* (55:3), pp. 175-188.

Garets, D. E., and Davis, M. 2006. "Electronic Medical Records vs. Electronic Health Records: Yes, There Is a Difference," White Paper, HIMSS Analytics™, Chicago, IL.

Gaskin, J., Berente, N., Lyytinen, K., and Yoo, Y. 2014. "Toward Generalizable Sociomaterial Inquiry: A Computational Approach for Zooming In and Out of Sociomaterial Routines," *MIS Quarterly* (38:3), pp. 849-871.

Goh, J. M., Gao, G., and Agarwal, R. 2011. "Evolving Work Routines: Adaptive Routinization of Information Technology in Heathcare," *Information Systems Research* (22:3), pp. 565-585.

Goo, J., Kishore, R., Rao, H. R., and Nam, K. 2009. "The Role of Service Level Agreements in Relational Management of Information Technology Outsourcing: An Empirical Study," *MIS Quarterly* (33:1), pp. 119-145.

Gottfredson, M., Puryear, R., and Phillips, S. 2005. "Strategic Sourcing from Periphery to the Core," *Harvard Business Review* (83:2), pp. 132-139.

Greenwood, R., and Hinings, C. R. 1996. "Understanding Radical Organizational Change: Bringing Together the Old and the New Institutionalism," *Academy of Management Review* (21:4), pp. 1022-1054.

Hambrick, D. C., and Mason, P. A. 1984. "Upper Echelons: The Organization as a Reflection of its Top Managers," *Academy of Management Review* (9:2), pp. 193-206.

Hannan, M. T., and Freeman, J. 1977. "The Population Ecology of Organizations," *American Journal of Sociology* (82:5), pp. 929-964.

Hannan, M. T., and Freeman, J. 1984. "Structural Inertia and Organizational Change," *American Sociological Review* (49:2), pp. 149-164.

Hayes, R. H., Pisano, G. P., Upton, D. M., and Wheelwright, S. C. 2005. *Operations, Strategy, and Technology: Pursuing the Competitive Edge* (1st ed.), New York: John Wiley & Sons.

HealthIT.gov 2015. "What Is an Electronic Medical Record (EMR)?" (http://www.healthit.gov/providers-professionals/electronic-medical-records-emr).

Herfindahl, O. C. 1950. *Concentration in the U.S. Steel Industry*, Dissertation, New York: Columbia University.

HIMSS Analytics. 2015. "HIMSS Analytics" (http://www.himssanalytics.org/data/HADB).

Hox, J. J. 1995. *Applied Multilevel Analysis* (1st ed.), Amsterdam: TT-Publikaties.

IBISWorld. 2014. "Industry Report OD4172: Electronic Medical Records Systems in the US."

Jenkins, K. 2015. "The Risks of Having a Multi-Vendor Strategy," Scorpion Healthcare Internet Marketing (http://www.scorpionhealthcare.com/Our-Blog/2015/May/The-Risks-of-Having-a-Multi-Vendor-Strategy.aspx).

Johnson, V. 2007. "What Is Organizational Imprinting? Cultural Entrepreneurship in the Founding of the Paris Opera," *American Journal of Sociology* (113:1), pp. 97-127.

Joynt, K. E., Orav, E. J., and Jha, A. K. 2014. "Association between Hospital Conversions to For-Profit Status and Clinical and Economic Outcomes," *Journal of the American Medical Association* (312:16), pp. 1644-1652.

Kalorama Information. 2014. "EMR Markets 2014."

Karim, J., Somers, T. M., and Bhattacherjee, A. 2007. "The Impact of ERP Implementation on Business Process Outcomes: A Factor-Based Study," *Journal of Management Information Systems* (24:1), pp. 101-134.

Kellermann, A. L., and Jones, S. S. 2013. "What it Will Take to Achieve the As-Yet-Unfulfilled Promises of Health Information Technology," *Health Affairs* (32:1), pp. 63-68.

Kelley, K., and Preacher, K. J. 2012. "On Effect Size," *Psychological Methods* (17:2), pp. 137-152.

Kelly, D., and Amburgey, T. L. 1991. "Organizational Inertia and Momentum: A Dynamic Model of Strategic Change," *Academy of Management Journal* (34:3), pp. 591-612.

Kumar, S., and Aldrich, K. 2010. "Overcoming Barriers to Electronic Medical Record (EMR) Implementation in the US Healthcare System: A Comparative Study," *Health Informatics Journal* (16:4), pp. 306-318.

Kumar, V., Maheshwari, B., and Kumar, U. 2003. "An Investigation of Critical Management Issues in ERP Implementation: Empirical evidence from Canadian organizations," *Technovation* (23:10), pp. 793-807.

Lacity, M. C., Khan, S. A., and Willcocks, L. P. 2009. "A Review of the IT Outsourcing Literature: Insights for Practice," *Journal of Strategic Information Systems* (18:3), pp. 130-146.

Lacity, M. C., and Willcocks, L. P. 1998. "An Empirical Investigation of Information Technology Sourcing Practices: Lessons from Experience," *MIS Quarterly* (22:3), pp. 363-408.

Lamb, J. 2008. "Legacy Systems Continue to Have a Place in the Enterprise," ComputerWeekly.com (http://www.computerweekly.com/feature/Legacy-systems-continue-to-have-a-place-in-the-enterprise).

Larson, P. D., and Kulchitsky, J. D. 1998. "Single Sourcing and Supplier Certification: Performance and Relationship Implications," *Industrial Marketing Management* (27:1), pp. 73-81.

Lee, J., McCullough, J. S., and Town, R. J. 2013. "The Impact of Health Information Technology on Hospital Productivity," *RAND Journal of Economics* (44:3), pp. 545-568.

Levenshtein, V. I. 1966. "Binary Codes Capable of Correcting Deletions, Insertions, and Reversals," *Soviet Physics Doklady* (10:8), pp. 707-710.

Levina, N., and Su, N. 2008. "Global Multisourcing Strategy: The Emergence of a Supplier Portfolio in Services Offshoring," *Decision Sciences* (39:3), pp. 541-570.

Li, C. H., and Debo, L. G. 2009. "Second Sourcing vs. Sole Sourcing with Capacity Investment and Asymmetric Information," *Manufacturing & Service Operations Management* (11:3), pp. 448-470.

Light, B., Holland, C. P., and Wills, K. 2001. "ERP and Best of Breed: A Comparative Analysis," *Business Process Management Journal* (7:3), pp. 216-224.

McCullough, J. S., Casey, M., Moscovice, I., and Prasad, S. 2010. "The Effect of Health Information Technology on Quality in U.S. Hospitals," *Health Affairs* (29:4), pp. 647-654.

Melnick, G. A., and Fonkych, K. 2016. "Hospital Prices Increase in California, Especially Among Hospitals in the Largest Multi-Hospital Systems," *Inquiry* (53), pp. 1-7.

Meyer, J. W., and Rowan, B. 1977. "Institutionalized Organizations: Formal Structure as Myth and Ceremony," *American Journal of Sociology* (83), pp. 440-463.

Mintzberg, H. 1978. "Patterns in Strategy Formation," *Management Science* (24:9), pp. 934-948.

Mishra, A. K., and Tadikamalla, P. R. 2006. "Order Splitting in Single Sourcing with Scheduled-Release Orders," *Journal of the Operational Research Society* (57:2), pp. 177-189.

ONC. 2016. "About ONC," Office of the National Coordinator for Health Information Technology, HealthIT.gov (https://www.healthit.gov/newsroom/about-onc).

Pache, A.-C., and Santos, F. 2010. "When Worlds Collide: The Internal Dynamics of Organizational Responses to Conflicting Institutional Demands," *Academy of Management Review* (35:3), pp. 455-476.

Peng, G., Dey, D., and Lahiri, A. 2014. "Healthcare IT Adoption: An Analysis of Knowledge Transfer in Socioeconomic Networks," *Journal of Management Information Systems* (31:3), pp. 7-34.

Pentland, B. T. 2003a. "Conceptualizing and Measuring Variety in the Execution of Organizational Work Processes," *Management Science* (49:7), pp. 857-870.

Pentland, B. T. 2003b. "Sequential Variety in Work Processes," *Organization Science* (14:5), pp. 528-540.

Pettengill, J., and Vertrees, J. 1982. "Reliability and Validity in Hospital Case-Mix Measurement," *Health Care Financing Review* (4:2), pp. 101-128.

Porter, M. E. 1985. *Competitive Advantage* (1st ed.), New York: Free Press.

R Core Team. 2016. "R: A Language and Environment for Statistical Computing," R Foundation for Statistical Computing, Vienna, Austria.

Ramasubbu, N., Mithas, S., Krishnan, M. S., and Kemerer, C. F. 2008. "Work Dispersion, Process-Based Learning, and Offshore Software Development Performance," *MIS Quarterly* (32:2), pp. 437-458.

Ray, G., Muhanna, W. A., and Barney, J. B. 2005. "Information Technology and the Performance of the Customer-Service Process: A Resource-Based Analysis," *MIS Quarterly* (29:4), pp. 625-652.

Richardson, J. 1993. "Parallel Sourcing and Supplier Performance in the Japanese Automobile Industry," *Strategic Management Journal* (14:5), pp. 339-350.

Richardson, J., and Roumasset, J. 1995. "Sole Sourcing, Competitive Sourcing, Parallel Sourcing: Mechanisms for Supplier Performance," *Managerial and Decision Economics* (16:1), pp. 71-84.

Rogers, E. M. 2003. *Diffusion of Innovations* (5th ed.), New York: Free Press.

Roskill, J. 2014. "Here We Go Again: Single ERP Integration vs. Best of Breed Functionality," Acumatica, July 15 (http://www.acumatica.com/here-we-go-again-single-erp-integration-vs-best-of-breed-functionality/).

Rosko, M. D., and Chilingerian, J. A. 1999. "Estimating Hospital Inefficiency: Does Case Mix Matter?," *Journal of Medical Systems* (23:1), pp. 57-71.

Ruef, M., and Scott, W. R. 1998. "A Multidimensional Model of Organizational Legitimacy: Hospital Survival in Changing Institutional Environments," *Administrative Science Quarterly* (43:4), pp. 877-904.

Sabherwal, R., and Robey, D. 1993. "An Empirical Taxonomy of Implementation Processes Based on Sequences of Events in Information System Development," *Organization Science* (4:4), pp. 548-576.

Schneider, A. 2013. "When Companies Become Prisoners of Legacy Systems," *The Wall Street Journal* (http://deloitte.wsj.com/cio/2013/10/01/when-companies-become-prisoners-of-legacy-systems/).

Scott, W. R. 1987. "The Adolescence of Institutional Theory," *Administrative Science Quarterly* (32:4), pp. 493-511.

Sherer, P. D., and Lee, K. 2002. "Institutional Change in Large Law Firms: A Resource Dependency and Institutional Perspective," *Academy of Management Journal* (45:1), pp. 102-119.

Silva, L., and Hirschheim, R. A. 2007. "Fighting Against Windmills: Strategic Information Systems and Organizational Deep Structures," *MIS Quarterly* (31:2), pp. 327-354.

Singer, J. D., and Willett, J. B. 2003. *Applied Longitudinal Data Analysis: Modeling Change and Event Occurrence* (1st ed.), New York: Oxford University Press.

Spaulding, T. J., Furukawa, M. F., Raghu, T. S., and Vinze, A. 2013. "Event Sequence Modeling of IT Adoption in Healthcare," *Decision Support Systems* (55:2), pp. 428-437.

Stinchcombe, A. L. 1965. "Organizations and Social Structure," in *Handbook of Organizations,* J. G. March (ed.), Chicago: Rand McNally, pp. 153-193.

Sturgeon, J. 2007. "Stew on This: Case Mix Basics," *For the Record* (10:11), p. 6.

Suchman, M. C. 1995. "Managing Legitimacy: Strategic and Institutional Approaches," *Academy of Management Review* (20:3), pp. 571-610.

Sydow, J., Schreyögg, G., and Koch, J. 2009. "Organizational Path Dependence: Opening the Black Box," *Academy of Management Review* (34:4), pp. 689-709.

Tolbert, P. S., and Zucker, L. G. 1983. "Institutional Sources of Change in the Formal Structure of Organizations: The Diffusion of Civil Service Reform, 1880-1935," *Administrative Science Quarterly* (28:1), pp. 22-39.

Vibert, C. 2004. *Theories of Macro Organizational Behavior: A Handbook of Ideas and Explanations* (1st ed.), Armonk, NY: M. E. Sharpe.

Zhu, K., Kraemer, K. L., and Xu, S. 2006. "The Process of Innovation Assimilation by Firms in Different Countries: A Technology Diffusion Perspective on e-Business," *Management Science* (52:10), pp. 1557-1576.

About the Authors

Corey M. Angst is the Viola D. Hank Associate Professor in the IT, Analytics, and Operations Department at the Mendoza College of Business, University of Notre Dame. His research interests are in the transformational effect of IT, technology usage, IT value, and privacy of information. Angst has held various editorial roles and his research has been published in top journals across diverse disciplines including information systems, healthcare informatics, policy, operations, and strategy. He received his Ph.D. from the Smith School of Business, University of Maryland.

Kaitlin D. Wowak is an assistant professor in the IT, Analytics, and Operations Department at the Mendoza College of Business, University of Notre Dame. Her research interests are in strategic supply chain management, with a focus on product recalls and supply chain knowledge. Her research has been published (or is forthcoming) in *MIS Quarterly*, *Strategic Management Journal*, *Decision Sciences*, *Journal of Supply Chain Management, Journal of Business Logistics*, *Communications of the Association for Information Systems*, and *IEEE Transactions on Engineering Management*. She received her Ph.D. from the Smeal College of Business, Pennsylvania State University.

Sean M. Handley is an associate professor in the IT, Analytics, and Operations Department at the Mendoza College of Business, University of Notre Dame. His primary scholarly interests lie in studying formal and informal mechanisms for managing interorganizational relationships, the management of offshore outsourcing engagements, and quality management with outsourced manufacturing. Sean is a member of multiple editorial review boards and his research has been published in several leading journals. He obtained his Ph.D. from the Fisher College of Business, The Ohio State University.

Ken Kelley is a professor of Information Technology, Analytics, and Operations (ITAO) and the Associate Dean for Faculty and Research in the Mendoza College of Business at the University of Notre Dame. Ken's work is on quantitative methodology, where he focuses on the development, improvement, and evaluation of statistical methods and measurement issues. His specialties are in the areas of research design, effect size estimation and confidence interval formation, longitudinal data analysis, and statistical computing. In addition to his methodological work, Ken collaborates with colleagues on a variety of important topics applying methods. He is an Accredited Professional Statistician™ (PStat®) by the American Statistical Association, associate editor of *Psychological Methods*, recipient of the Anne Anastasi early career award by the American Psychological Association's Division of Evaluation, Measurement, & Statistics, and a fellow of the American Psychological Association.

MIS Quarterly

RESEARCH ARTICLE

ANTECEDENTS OF INFORMATION SYSTEMS SOURCING STRATEGIES IN U.S. HOSPITALS: A LONGITUDINAL STUDY

Corey M. Angst, Kaitlin D. Wowak, Sean M. Handley, and Ken Kelley
IT, Analytics, and Operations Department, University of Notre Dame, Mendoza College of Business,
Notre Dame, IN 46556 U.S.A.
{cangst@nd.edu} {katie.wowak@nd.edu} {shandley@nd.edu} {kkelley@nd.edu}

Appendix

Levenshtein Distance and adist

Levenshtein distance is a measure of the similarity between two strings. The R function, *adist*, calculates Levenshtein distance by computing the minimal possibly weighted number of insertions, deletions and substitutions needed to transform one string into another. The function as implemented in R is

adist(x, y = NULL, costs = NULL, counts = FALSE, fixed = TRUE, partial = !fixed, ignore.case = FALSE, useBytes = FALSE)

where

x = a character vector. Long vectors are not supported.
y = a character vector, or NULL (default) indicating taking x as y.
costs = a numeric vector or list with names partially matching insertions, deletions and substitutions giving the respective costs for computing the Levenshtein distance, or NULL (default) indicating using unit cost for all three possible transformations.
counts = a logical indicating whether to optionally return the transformation counts (numbers of insertions, deletions and substitutions) as the “counts” attribute of the return value.
fixed = a logical. If TRUE (default), the x elements are used as string literals. Otherwise, they are taken as regular expressions and partial = TRUE is implied (corresponding to the approximate string distance used by agrep with fixed = FALSE.
partial = a logical indicating whether the transformed x elements must exactly match the complete y elements, or only substrings of these. The latter corresponds to the approximate string distance used by agrep (by default).
ignore.case = a logical. If TRUE, case is ignored for computing the distances.
useBytes = a logical. If TRUE distance computations are done byte-by-byte rather than character-by-character.

Example:

Distance from AAAAB to AAAAA. Number of substitutions = 1 (substitute B for A). Then for the *Adjusted* score, we normalize by dividing *adist* by the number of modules adopted (ranges from 2 to 5) and subtract it from 1. Thus, the score is 1 – 1/5 = 0.80. The *unadjusted* distance always divides by 5, so in this example, both are 1 – 1/5 = 0.80.

Adjusted distance from CAAB– to AAAAA. Number of substitutions = 2 (substitute C and B for A), so the score is 1 – 2/4 = 0.50; Note that because the sequence length is 4 (i.e., one missing), there is no insertion.

Unadjusted distance from CAAB– to AAAAA. Number of substitutions = 2 (substitute C and B for A), Number of insertions= 1 (from missing [–] to A), so the score is 1 – 3/5 = 0.40.

Table A1. Actual Sequences Used by Hospitals and Associated Closeness Scores

Actual Sequence	Adjusted Closeness	Unadjusted Closeness	Actual Sequence	Adjusted Closeness	Unadjusted Closeness	Actual Sequence	Adjusted Closeness	Unadjusted Closeness
AAAAA[1]	1.00	1.00	-A-BA	0.67	0.40	A-BZ-	0.33	0.20
AAAA-	1.00	0.80	ABAB-	0.50	0.40	AC-B-	0.33	0.20
A-AAA	1.00	0.80	ABAC-	0.50	0.40	-ACB-	0.33	0.20
-AAAA	1.00	0.80	ABBA-	0.50	0.40	ADBC-	0.25	0.20
AAAAB	0.80	0.80	ABBAC	0.40	0.40	AZ- - -	0.50	0.20
AAABA	0.80	0.80	ABCA-	0.50	0.40	A- -Z-	0.50	0.20
AABAA	0.80	0.80	ABZA-	0.50	0.40	-A-Z-	0.50	0.20
ABAAA	0.80	0.80	ACAB-	0.50	0.40	BA- - -	0.50	0.20
BAAAA	0.80	0.80	A-CAB	0.50	0.40	B- -A-	0.50	0.20
AAA- -	1.00	0.60	ACBA-	0.50	0.40	-BA- -	0.50	0.20
AA-A-	1.00	0.60	ADACB	0.40	0.40	-B-A-	0.50	0.20
AA- -A	1.00	0.60	ADCBA	0.40	0.40	- -BA-	0.50	0.20
A-AA-	1.00	0.60	AZ-A-	0.67	0.40	- - -BA	0.50	0.20
A- -AA	1.00	0.60	AZAB-	0.50	0.40	BA-C-	0.33	0.20
-AAA-	1.00	0.60	AZBA-	0.50	0.40	BA-Z-	0.33	0.20
-A-AA	1.00	0.60	BA-A-	0.67	0.40	-BAZ-	0.33	0.20
- -AAA	1.00	0.60	B-AA-	0.67	0.40	-BCA-	0.33	0.20
AAAB-	0.75	0.60	-BAA-	0.67	0.40	BZ-A-	0.33	0.20
AA-AB	0.75	0.60	-B-AA	0.67	0.40	BZCA-	0.25	0.20
AABA-	0.75	0.60	BAAB-	0.50	0.40	CA-B-	0.33	0.20
AACAB	0.60	0.60	BABA-	0.50	0.40	C-AB-	0.33	0.20
ABAA-	0.75	0.60	B-AZA	0.50	0.40	-CAB-	0.33	0.20
AB-AA	0.75	0.60	BBAA-	0.50	0.40	CB-A-	0.33	0.20
ABABA	0.60	0.60	BCAA-	0.50	0.40	-CBA-	0.33	0.20
AZAA-	0.75	0.60	BC-AA	0.50	0.40	Z-A- -	0.50	0.20
BAAA-	0.75	0.60	CAAB-	0.50	0.40	Z- -A-	0.50	0.20
BCAAA	0.60	0.60	-CAAB	0.50	0.40	-Z-A-	0.50	0.20
CAAAB	0.60	0.60	CBAA-	0.50	0.40	- -ZA-	0.50	0.20
ZAAA-	0.75	0.60	CDAAB	0.40	0.40	ZA-B-	0.33	0.20
AA- - -	1.00	0.40	ZA-A-	0.67	0.40	-Z-AB	0.33	0.20
A-A- -	1.00	0.40	Z-AA-	0.67	0.40	ZA-BC	0.25	0.20
-AA- -	1.00	0.40	ZABA-	0.50	0.40	Z-AZ-	0.33	0.20
-A-A-	1.00	0.40	ZBAA-	0.50	0.40	ZAZZ-	0.25	0.20
- -AA-	1.00	0.40	ZZAA-	0.50	0.40	ZB-A-	0.33	0.20
- - -AA	1.00	0.40	A- - - -[2]	1.00	0.20	ZBCA-	0.25	0.20
AA-B-	0.67	0.40	-A- - -	1.00	0.20	ZB-ZA	0.25	0.20
A-AB-	0.67	0.40	- -A- -	1.00	0.20	ZZA- -	0.33	0.20
A- -AB	0.67	0.40	- - -A-	1.00	0.20	ZZ-A-	0.33	0.20
AABB-	0.50	0.40	AB- - -	0.50	0.20	ABCDE[3]	0.20	0.20
AA-BC	0.50	0.40	A-B- -	0.50	0.20	ZZBA-	0.25	0.20
AAZ- -	0.67	0.40	A- -B-	0.50	0.20	ZZZA-	0.25	0.20
A-AZ-	0.67	0.40	-A-B-	0.50	0.20	Z- - - -	0.00	0.00
ABA- -	0.67	0.40	- -AB-	0.50	0.20	Z- -Z-	0.00	0.00
AB-A-	0.67	0.40	AB-C-	0.33	0.20	-Z-Z-	0.00	0.00

[1] We define this as the “target” prototypical single-sourcing sequence.
[2] While this sequence was present in our dataset, it was not used in the analysis because empirically we do not view the sourcing decision of a single module as being indicative of a sourcing strategy.
[3] We define this as a prototypical multisourcing sequence.

Table A2. Descriptives for *Unadjusted* Closeness to Single-Sourcing Variable

Year	2005	2006	2007	2008	2009	2010	2011	2012	2013
Mean (StdDev)	0.439 (0.209)	0.514 (0.260)	0.593 (0.283)	0.632 (0.286)	0.691 (0.272)	0.720 (0.274)	0.736 (0.271)	0.790 (0.274)	0.820 (0.253)

Table A3. Mixed Effects Regression Results with *Unadjusted* Closeness to Single-Sourcing as DV

		Model Number and Description					
	Parameter	**1 Intercept Only**	**2 + Slope**	**3 + Strategic Orientation**	**4 + Formal Structure**	**5 + Internal Dynamics**	**6 + Interactions**
	Intercept	0.686*** (0.003)	0.515*** (0.004)	0.545*** (0.005)	0.541*** (0.005)	0.533*** (0.017)	0.424*** (0.026)
Control Variables	Slope (YearSince2005)		0.041*** (0.001)	0.041*** (0.001)	0.041*** (0.001)	0.042*** (0.001)	0.068*** (0.005)
Control Variables	For-Profit (FP)			-0.103*** (0.007)	-0.085** (0.007)	-0.058*** (0.008)	-0.024* (0.010)
Control Variables	Teaching (Teach)			0.069*** (0.013)	0.034* (0.014)	0.039* (0.014)	0.019 (0.018)
Control Variables	Hospital Size (ln_StfBed)				0.016*** (0.003)	0.010* (0.004)	-0.014* (0.006)
Control Variables	System Size (ln_SysSize)				-0.015*** (0.001)	-0.014*** (0.002)	-0.004† (0.002)
Control Variables	Hospital Age (lnAge)				0.005 (0.004)	0.009* (0.004)	0.018*** (0.005)
Control Variables	Case Complexity (CMI)					-0.000 (0.013)	0.074*** (0.019)
Control Variables	lnAge × YearSince2005						-0.003*** (0.0009)
Interactions of Interest	FP × YearSince2005						-0.008*** (0.002)
Interactions of Interest	Teach × YearSince2005						0.004 (0.003)
Interactions of Interest	ln_StfBed × YearSince2005						0.006*** (0.001)
Interactions of Interest	ln_SysSize × YearSince2005						-0.003*** (0.0004)
Interactions of Interest	CMI × YearSince2005						-0.017*** (0.003)
	Pseudo-R^2	.528	.788	.786	.786	.770	.771
	Model Comparison		2 vs. 1 $\chi^2(3) = 12410$***				6 vs. 5 $\chi^2(6) = 168$***
	n-Hospitals	3,417	3,417	3,322	3,318	2,824	2,824
	n-Observations	29,033	29,033	28,241	28,210	22,809	22,809
	LL	-894	5305	5854	5926	5077	5126

†$p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Copyright of MIS Quarterly is the property of MIS Quarterly and its content may not be copied or emailed to multiple sites or posted to a listserv without the copyright holder's express written permission. However, users may print, download, or email articles for individual use.