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ORIGINAL ARTICLE

Strategic sourcing of multicomponent software systems: The case of electronic medical records

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Abstract
The significance of information technology (IT) to organizational performance is increasingly acknowledged by senior executives and scholars alike. However, an important aspect that is underdeveloped in the extant literature is whether and how an organization's IT *sourcing strategy* affects performance. We examine this dimension in the context of hospitals' sourcing strategy for electronic medical record (EMR) systems. Leveraging the organization-IT alignment principle grounded in contingency theory, we argue that the sourcing strategy chosen by hospitals impacts the quality of patient care rendered and that the nature of this relationship has changed over time. Using data on US hospitals that operated continuously from 2006 to 2013 and employing a multilevel longitudinal modeling framework to analyze change over time, we examine how a key dimension of the sourcing strategy for EMR systems—change in closeness to single-sourcing—impacts conformance quality, a critical measure of hospital performance that assesses how frequently hospitals comply with evidence-based practices. We find that a change closer to single-sourcing is positively associated with conformance quality, but this positive effect is reduced over time, meaning that the benefits realized by hospitals using a single-sourcing approach diminish toward the end of our observation period. As explicated in our discussion of results, findings from our research reveal critical insights about how sourcing decisions impact performance, and how these effects evolve over time due to changes in regulations, technology, and competition.

KEYWORDS
conformance quality, contingency theory, electronic medical records, health IT, hospitals, strategic sourcing, within-between mixed-effects model

1 | INTRODUCTION

The majority of research on the business value of information technology (IT) has focused on the performance implications of adopting IT systems (Atasoy et al., 2018). However, it is not necessarily *if* a particular IT is adopted, but instead, *how* the IT is adopted and managed that matters to organizational performance (Angst et al., 2017a; Devaraj & Kohli, 2003; Ross & Weill, 2011). This is particularly true for complex multicomponent software systems (e.g., enterprise resource planning systems) that are present in many organizations. Multicomponent systems require more oversight, integration, and maintenance than stand-alone software systems (Sodero et al., 2013). Organizations, for example, have to make a number of strategic sourcing decisions, such as selecting supplier(s) for each of the components in the system and weighing the tradeoffs associated with integrating new components into existing software suites. As Van de Vrande (2013, p. 611) writes, "[as] technology sourcing [is] becoming more important, the composition of the sourcing portfolio becomes a vital aspect of a firm's competitive strategy and [is] likely to determine its future competitive advantage."

We leverage contingency theory (Donaldson, 2001; Lawrence & Lorsch, 1967) and key tenets from modularity logic (Furlan et al., 2014; Schilling, 2000) to examine whether and how an organization's sourcing strategy for multicomponent software systems impacts its performance. Contingency theory suggests that there is no single best way to structure an organization (Lawrence & Lorsch, 1967). Rather, organizational performance depends on the degree

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of “fit” between organizational structures, processes, or routines and the environment (Terjesen et al., 2012). There is a rich history of using contingency logic to examine how the alignment (or misalignment) between the structure of an organization’s IT and its routines, tasks, environment, etc. influences performance (Zigurs & Buckland, 1998). A consideration that is particularly germane to this organization-IT alignment in the context of sourcing multicomponent products and systems is the degree to which the systems’ architecture is modular, meaning that the components are loosely coupled and can, therefore, be mixed and matched easily (Schilling, 2000). As such, contingency theory and modularity logic are well-suited for examining how the sourcing of multicomponent software systems impacts performance.

We focus on the sourcing decisions for electronic medical record (EMR) systems in US hospitals. EMR suites are multicomponent software systems that manage patients’ electronic medical records at health care delivery organizations and allow health care providers to document and monitor health care delivery (Ding & Peng, 2020). The EMR market is competitive with multiple suppliers and, thus, there is significant variation in supplier choices and sourcing strategies across hospitals (IBISWorld, 2014; Payne et al., 2012). Subsequently, hospitals can source individual EMR components or complete EMR suites from a wide variety of suppliers. Hospitals can, for example, source all EMR components in a suite from a single supplier (single-sourcing, hereafter, “SS”), which enhances interoperability across components (i.e., minimizes intercomponent misalignment). In this context, interoperability represents the capability to send, receive, query, and use data that is electronically exchanged across components (Dixon et al., 2020). Alternatively, hospitals can source individual EMR components from multiple different suppliers (multisourcing, hereafter, “MS”), which improves the alignment between existing organizational routines, clinician preferences, and the structures embedded in the software (i.e., minimizes organization-IT misalignment).

Our focus on EMR systems is motivated by three factors. First, there is widespread adoption of EMRs across the health care industry (Dobrzykowski & Tarafdar, 2017; IBISWorld, 2014). Second, there is an equivocal connection between EMR adoption and hospital performance in the literature (Angst et al., 2011; Ding & Peng, 2020; Dobrzykowski & Tarafdar, 2017; Gardner et al., 2015; Queenan et al., 2011; Smith et al., 2013). Third, nonintegrated EMR components (sometimes called “stand-alone” components) are cumbersome for health care providers to navigate and could potentially impact the quality of care provided (Sullivan, 2018), which was validated via firsthand observation of a provider by the author team.

In fact, this study was motivated, in part, by an observation made by the authors, when conducting an on-site research visit, of a cardiologist at a medium-sized regional hospital in the Midwest. At the beginning of each patient exam, he (the cardiologist) had to access one component of the hospital’s EMR system to confirm the patient’s general information. Because the hospital’s EMR system only allowed for one component to be accessed at a time and the components were not integrated, the doctor had to log out of the first component and log into another component—using a different username and password—to review the patient’s current medications. The doctor would then verify the list of current medications with the patient, and write the medicine names and dosages down on a piece of paper. Following this, he would log out of that component and log into a separate decision support system that identified medication interactions. After confirming that there were no potentially dangerous interactions, he logged out of the decision support system and logged into another EMR component while performing the exam. For the latter EMR component, the doctor did not like the capabilities of the component that came as part of the enterprise EMR, so he accessed an entirely different system. During discussions with the doctor, he confirmed “it wasn’t optimal” to use EMR components that did not integrate with each other and acknowledged that switching between components was not only inefficient, but also increased the potential for errors. While some doctors, such as this cardiologist, prefer a multisourcing approach to minimize the misalignment between existing organizational routines and the structures embedded in the software components (i.e., organization-IT misalignment), other doctors prefer sourcing all components from a single supplier to minimize intercomponent misalignment and improve interoperability. The focus of our study is to understand how these different EMR sourcing strategies, and, thus, different forms of alignment or misalignment, impact the quality of patient care provided.

In addition to commercial EMRs, some systems are developed internally by the hospital. However, most health care providers are increasingly sourcing EMRs from commercial suppliers, rather than developing applications internally (Classen & Bates, 2011); therefore, understanding the implications of these sourcing decisions on hospital performance is an important research topic. While our focus in this study is not directly related to noncommercial EMR components, our analyses do account for their presence.

Consistent with past scholarship (Senot et al., 2016; Sharma et al., 2016), we measure performance in terms of conformance quality (CQ), which represents a caregiver’s adherence to evidence-based standards of care during health care delivery, as documented on the patient’s EMR. It has been shown that if caregivers follow these guidelines, patient health is improved (Chassin et al., 2010). We posit that the EMR sourcing strategy impacts CQ, which is an important outcome, but has not been considered in the context of sourcing strategy. We further posit that the relationship between these sourcing decisions and a hospital’s performance changes over time. Specifically, environmental changes (e.g., passing of regulations, advancements in technology, etc.) may influence the type and extent of misalignment (i.e., organization-IT or intercomponent) a hospital should prioritize in order to improve the quality of care provided. As such, the research questions we examine are: *Do hospitals’ movements toward a single-sourcing EMR configuration or* *a multisourcing EMR configuration yield larger performance improvements, and how has this relationship changed over time?*

Leveraging a rich dataset that includes the EMRs component-level sourcing decisions and CQ scores of US hospitals from 2006 to 2013, we use a "within-between" specification (Certo et al., 2017; Freeman et al., 2020; Mundlak, 1978) in a mixed-effects modeling framework (Gelman & Hill, 2006; McNeish & Kelley, 2019) to investigate these questions in the context of between-hospital differences and within-hospital change. As not all hospitals have the same operations or are as far along in terms of IT strategy as others, we control for hospitals' closeness to SS at the starting point of entry into the study (the between-hospital value), while hypothesizing how hospitals change from their starting point toward or away from SS (the within value) impacts CQ. Consequently, our theorizing centers on within-hospital variation. Our modeling approach has several advantages, including explicitly controlling for potential omitted variable bias at the hospital level, which addresses endogeneity issues for hospital characteristics that are not included in the model (Allison, 2009; Bell & Jones, 2015; Ketokivi & McIntosh, 2017; Lu et al., 2018; McNeish & Kelley, 2019). We find that a move closer toward SS is positively associated with CQ, but this effect lessens in the latter years of our observation period. Numerous robustness checks further validate these findings.

Our study makes several important contributions to the literature at the operations-IT interface. Most notably, this study contributes much needed insight to the performance implications of an organization's sourcing strategy for multicomponent software systems, which are increasingly prevalent in modern organizations. IT is increasingly central to organizational strategy (Danoesastro et al., 2017; Siebel, 2017), but evidence regarding the linkage between IT adoption and performance remains mixed (Ding & Peng, 2020). This ambiguity suggests that other factors play a salient role in the IT adoption-performance relationship and need to be explicated. The observation that much of organizations' IT is sourced from commercial suppliers makes it apparent that a vitally important aspect of an organization's IT strategy that warrants further investigation is how the technology is sourced in order to minimize either organization-IT misalignment or intercomponent misalignment. This is particularly true in the context of EMRs, in which the evidence regarding the relationship between adoption of multicomponent EMRs and hospital performance is mixed, leaving important unresolved questions (Agarwal et al., 2010; Dobrzykowski & Tarafdar, 2017). This research illustrates the impact that moving closer toward SS has on CQ, and in so doing, establishes a foundation for future research.

Our results also provide new evidence that the performance impact of a sourcing strategy for multicomponent software systems is not static, but rather evolves over time with environmental changes. This finding offers insights to researchers and practitioners alike. For researchers, this finding stresses the importance of adopting a longitudinal perspective when examining the effectiveness of an organization's sourcing strategy. To better understand how our findings inform decisions by hospital administrators and other practitioners, we interviewed six key informants who have extensive experience in requirements analysis, technology selection, implementation, after-sales service, and actual use of EMR software. These interviews were conducted after the empirical results were known, which helped us ground our research findings in practice. We introduce these insights in the Discussion and Conclusion section.

2 | RELATED LITERATURE AND BACKGROUND

2.1 | IT in health care operations

A significant body of work has investigated relationships between health IT, hospital operations, and performance. This literature has primarily examined whether and how the *adoption* of health IT systems influences a hospital's operations and patient care (e.g., Angst et al., 2011; Atasoy et al., 2018; Gardner et al., 2015; Queenan et al., 2011). A subset of this scholarship has positioned health IT as a moderator of other relationships, such as that between hospital complexity and experiential quality (Peng et al., 2020) or how augmented clinical health IT moderates the relationship between clinical health IT systems and performance (Sharma et al., 2016). Additional studies examine how the effect of EMR use on physician performance and provider-patient communication is mediated by other factors (Dobrzykowski & Tarafdar, 2015; Dobrzykowski & Tarafdar, 2017). Although these prior contributions have made great strides in elucidating our understanding of the role of health IT, the linkage with patient care remains ambiguous (Agarwal et al., 2010; Dobrzykowski & Tarafdar, 2017).

Because of the mixed evidence for the influence of health IT adoption on performance, researchers have begun to examine implementation factors that might affect this relationship. One such thread of research looks at how EMRs are sourced from commercial suppliers—specifically, whether hospitals pursue a SS or MS configuration. If all the components in an EMR suite are provided by a single supplier, the hospital is using a prototypical SS configuration (Ford et al., 2010). Conversely, if a hospital sources the components in an EMR suite from more than one supplier, it is using a MS configuration[1] (Ford et al., 2010). The most extreme MS configuration is when each component within the EMR suite is provided by a different supplier.[2]

Angst et al. (2017b) examine how a hospital's strategic orientation, formal structure, and internal dynamics influence its migration along this sourcing continuum—namely, toward or away from a SS configuration. Nair and Dreyfus (2018)

[1] This strategy is also known as "best of breed" (Ford et al., 2010; Light et al., 2001; Roskill, 2014).

[2] See Figure A1 in Online Appendix A for a visual representation of a SS or MS configuration.

study the moderating effect of the sourcing strategy—referred to as IT adoption strategy by the authors—on the relationship between IT plan scope and meaningful use metrics. Our study is distinct from these two recent contributions in that we explicitly examine the direct relationship between EMRs sourcing strategy and a salient measure of hospital performance, which is potentially the missing link. Whereas Angst et al. (2017b) examined what factors lead to a SS strategy and Nair and Dreyfus (2018) examine the "meaningful use of technology" in the context of regulatory changes, the literature is glaringly absent in regard to technology's role on performance, particularly the degree to which hospitals are following best practices. Thus, our study fills in an important gap in the literature. In summary, while considerable progress has been made toward understanding how health IT systems influence health care operations, little is known about whether and how the sourcing configuration for these systems (i.e., where a hospital lies on this sourcing continuum) impacts the quality of patient care rendered, arguably the most important question in this context. Given that hospitals can pursue various EMR sourcing approaches, understanding the impact of such decisions on the quality of patient care provided is critical.

2.2 | Sourcing strategies for multicomponent products

Considerable scholarly work has examined product modularity (Colfer & Baldwin, 2016; Furlan et al., 2014; Ulrich, 1995) and sourcing strategies of multicomponent products (Li & Debo, 2009). While we build on this research, multicomponent software systems have important distinctions that limit the extent to which theoretical insights derived from studying other contexts (i.e., physical products) can transcend to the software environment. First, whereas sourcing components for physical products influences end-product performance, it does not necessarily impact broader organizational routines. However, as noted above, and further explicated in our hypotheses development below, we contend that an organization's sourcing choices for components in a software system significantly impact the type of misalignment that is minimized, which in turn impacts organizational routines. This broader impact of the sourcing strategy must be considered when trying to realize the IT system's full potential to improve performance outcomes.

A second distinction between multicomponent products and software systems relates to control over the product/system architecture. In much of the product modularity literature (for reviews see Campagnolo & Camuffo, 2010; Salvador, 2007), it is presumed that the focal firm largely controls the product architecture (such as specifying standardized component interfaces) and can focus on "choosing a supplier for each component and structuring the coordination between them" (Hoetker, 2006, p. 502). However, in the software industry, independent suppliers innovate and design their software to appeal to a broad market with potentially diverse

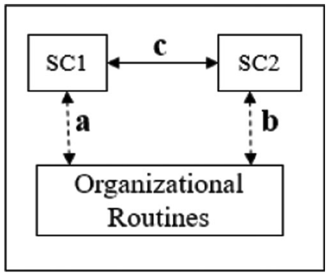

FIGURE 1 System of multiple software components and organizational routines

needs (Strong & Volkoff, 2010). Thus, absent significant integration investments, the extent to which any single firm can control how different supplier components interface with one another is limited by the extent to which industry standards of interoperability exist. Importantly, intercomponent misalignment must be considered as part of the sourcing decision. For these reasons, more research is needed to advance our understanding of sourcing multicomponent software systems, especially in the context of EMRs, which has considerable implications for patients.

2.3 | Organization-IT misalignment vs. intercomponent misalignment

In the case of multicomponent software systems, there are two types of alignment or misalignment issues that can impact performance (for simplicity, hereafter we will use the term "misalignment"). Figure 1 illustrates both types of misalignment for a relatively simple two-component software system. The first type is *organization-IT misalignment*. This reflects the differences between the structures embedded in the software components (i.e., SC1 or SC2) and the routines embedded in an organization—see interfaces "a" and "b" in Figure 1—whenever organizations use commercially sourced multicomponent software systems (Soh & Sia, 2004). Enterprise software systems are "designed to fit generic rather than specific requirements, and hence is likely to be an imperfect fit" with any organization's specific processes or routines (Strong & Volkoff, 2010, p. 731). Remedying the misalignment between the software system and existing routines often necessitates process reengineering efforts (Soh & Sia, 2004), which can negatively impact performance. The second potential type of misalignment with multicomponent software systems is *intercomponent misalignment*. Intercomponent misalignment emerges when components from different suppliers in an EMR suite face interoperability challenges—see interface "c" in Figure 1. Interoperability issues can also hinder performance. Because neither SS nor MS is unquestionably superior when considering both types of misalignment, below we present arguments supporting competing hypotheses for the relationship between a change in closeness to SS and CQ.

3 | HYPOTHESES

3.1 | Closeness to single-sourcing and performance

In line with contingency theory, we posit that there is no single best sourcing strategy for multicomponent software systems that minimizes both types of misalignment in all contexts. Rather, the sourcing strategies available to organizations pose a tradeoff related to these two forms of misalignment. Organizations can seek to minimize organization-IT misalignment (see interfaces “a” and “b” in Figure 1) through contingency theory’s differentiation approach (Lawrence & Lorsch, 1967) by selecting individual components from different suppliers[3] that most closely align with existing organizational routines. Lawrence and Lorsch (1967, p. 3–4) define differentiation as “the state of segmentation of the organizational system into subsystems, each of which tends to develop particular attributes in relation to the requirements posed by its relevant external environment.” Differentiation is the outcome of “local adoption to unit-specific tasks” (Terjesen et al., 2012, p. 308) and “specifies de-coupled interfaces between components” (Ulrich, 1995, p. 422). As such, differentiation is akin to modularity, where organizations build a “product or process from smaller subsystems that can be designed independently yet function together as a whole” (Baldwin & Clark, 1997).

Differentiation, in our context, is represented by a more extreme MS configuration or deviation from a prototypical SS configuration. A MS strategy allows hospitals to select each individual component from potentially different suppliers based upon its functionality and alignment with the existing needs, preferences, and routines of specific departments or clinical staff (Ford et al., 2010; Payne et al., 2012). In fact, the MS approach is often referred to as a “best of breed” (Light et al., 2001; Roskill, 2014) strategy because it allows each operating unit to select a component that best supports its needs, tasks, or existing routines. This better matching of system functionality to existing routines (i.e., fit) reduces process reengineering, operational disruption, and the need for retraining that often accompanies the integration of a SS suite (Ford et al., 2010; Ray et al., 2005). As a result, MS can improve the stability of operational routines, thereby supporting adherence to clinical processes and enhancing CQ (Anand et al., 2012). As a change toward more extreme MS represents a departure from SS, the preceding arguments suggest that CQ will be negatively associated with a move closer to SS. Thus, we hypothesize:

> *Hypothesis 1a: Moving closer to single-sourcing is negatively associated with conformance quality.*

[3] SC1 and SC2 represent Software Components for a hypothetical multicomponent software system. SC1 could be, for example, the Computerized Practitioner Order Entry component and SC2 the Physician Documentation component of an EMR suite.

Opposing arguments can also be made when considering the sourcing decision from the perspective of intercomponent misalignment (see interface “c” in Figure 1) and associated interoperability challenges. To help minimize this type of misalignment, organizations can leverage contingency theory’s integration approach (Lawrence & Lorsch, 1967). According to Lawrence and Lorsch (1967, p. 4), integration is “the process of achieving unity of effort among the various subsystems in the accomplishment of the organization’s task” and relies on the “coordination of interests and actions” among the components (Terjesen et al., 2012, p. 308).

In our context, integration is represented by a move closer toward the prototypical SS approach. From a modular systems perspective, it is reasoned that knowledge transfers, problem solving, and conflict resolution are more effectively handled when stronger ties exist among units doing different elements of the work—that is, caring for patients in our context (Colfer & Baldwin, 2016; Williamson, 1981). Thus, to the extent that the components of the system are interdependent and necessitate coordination—as with the different clinical routines and EMR components within a hospital—assigning work to fewer suppliers (i.e., closer to SS) would be advantageous (von Hippel, 1990). Because EMR components from a single supplier are designed to fit seamlessly together, there is increased interoperability among the components with this sourcing approach (Dixon et al., 2020), which can play an important role when trying to optimize performance across the entire hospital (Ford et al., 2010). If EMRs face interoperability issues, health care providers only have a partial picture of a patient’s medical history at the time of care, which can lead to suboptimal care. According to Payne et al. (2012, p. 465), “the greatest risk of multiple EMR use is the risk of missing data and any corresponding decision support that impact patient safety.” In other words, “there is no shared care record” (Hammadeh, 2018). Information about patients exists in multiple EMR components and if the components lack interoperability “no one has the complete picture of your [patient] health upon which to make treatment decisions or implement preventative courses of action” (Hammadeh, 2018). In fact, if EMR components lack interoperability, “as patients transfer between different locations or different levels of care within the same location” (Coleman, 2003, p. 549), “they [patients] often have to manage their own care” as their complete medical history may not follow them (Lim et al., 2015, p. 49).

As was evident in the authors’ direct observation of the aforementioned cardiologist’s workflow, interoperability issues are also taxing from health care providers’ perspectives. For example, providers “have to open a chain of applications pertaining to the contributing component to view the entire patient record” and are “required to log-in and out every time he or she switches from one application to other” (Kalorama Information, 2014, p. 46). Such processes can lead to safety and quality issues and ultimately, to inferior patient care because providers have to allocate more cognitive capacity to logging in and out of numerous applications needed in order to view the patient's entire medical record (Payne et al., 2012). Thus, less time and cognitive space is directed to understanding the patient's needs.

The interoperability afforded by SS allows health care providers to view a patient's entire medical history seamlessly and reduces the need for manual data entry and transmission, which is often linked to medical errors (Aron et al., 2011). It also provides clinicians with more complete and timely information at the point of care, reducing the risk of conducting unnecessary tests or procedures (Payne et al., 2012). Single-sourced EMRs can also reduce departmental silos, enhance communication, and support evidence-based decision-making by quickly and accurately sharing patient records between departments (Angst et al., 2017b; Payne et al., 2012). This can reduce the time it takes to reach a consensus about a patient's diagnosis and can increase the speed and quality of care provided. These arguments suggest a positive association between moving closer to SS and CQ. Thus, we hypothesize:

Hypothesis 1b: *Moving closer to single-sourcing is positively associated with conformance quality*.

3.2 | Moderating effect of time

In the previous section, we theorized that moving away from SS (i.e., more extreme MS) would be advantageous to performance due to minimizing the challenges posed by organization-IT misalignment, whereas moving closer toward SS would improve interoperability across components of an EMR and, thereby, better address the operational difficulties associated with intercomponent misalignment. Thus, in a global sense, the superiority of moving closer to, versus away from, SS rests with the relative significance of these competing challenges, as addressing one form of misalignment may exacerbate the other.

With our final hypothesis, we advance the argument that, in the context of sourcing EMR components, the relative significance of organization-IT misalignment vis-à-vis intercomponent misalignment is not static over time. Modular systems theory suggests that due to environmental changes the degree of system modularity is subject to change over time with many systems moving toward greater modularity (Schilling, 2000). Thus, environmental changes should also influence the effectiveness of a given sourcing strategy for the components of a system. In line with this logic, we posit that over the observation period of our study, the degree of interoperability difficulty associated with intercomponent misalignment has diminished while the benefits of aligning EMR components with the needs of specific departments or staff (i.e., by MS) persist. Relatedly, we contend that the general industry migration toward SS has reduced the competitive advantages available to hospitals that existed earlier in the timeframe under investigation (Angst et al., 2017b). As a result, we expect the relationship between a move closer to SS and CQ to be negatively moderated by time, meaning that the effect will be less or nonexistent later in the study period, but more salient early in the study period.

Our expectation that the interoperability challenges associated with intercomponent misalignment have diminished over time is predicated on observations of changes in the regulatory and technological landscape (Nair & Dreyfus, 2018). The Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009 is particularly relevant as it provides health care organizations with financial incentives if they adopt and demonstrate meaningful use (MU) of health IT systems, such as EMRs (HHS.gov, 2017).[4] The core objective of MU rests on several aspects, which include promoting interoperable EMR components to improve the exchange of electronic health information in hopes of enhancing the quality and efficiency of care (CDCP, 2017; Furukawa et al., 2014; Henricks, 2011). In other words, MU centers on improving care coordination between providers, which suggests that integration and interoperability requirements have increased with the HITECH Act.

Further, the Centers for Medicare and Medicaid Services, (CMS's) emphasis on improved information exchange and interoperability has continued to increase since the initial passage of the HITECH Act. For instance, in light of the somewhat disappointing progress made with the initial MU criteria, the Stage 2 MU (MU2) criteria announced in 2012 called for a "leap toward interoperability" (Mostashari, 2012). In fact, CMS later renamed its incentive program, now calling it "Promoting Interoperability" to align with its focus on improving health information exchange (Bresnick, 2018). Also included in MU2 were requirements for provider order entry, electronic prescribing, delivering decision support at the point of care, and providing patients with electronic access to their health information, all of which require seamless and efficient interaction and interoperability between components.[5]

Thus, it is clear that US Federal Government incentives for interoperability, and emphasis placed on a more seamless information exchange, has increased over time. This has spurred the health IT community to push toward greater standardization across EMR supplier technologies in areas such as data coding and communication protocols (AHRQ, 2017; Turk, 2016). As EMR suppliers standardize on data coding and communication protocols, the challenge of making EMR components from different suppliers interoperable is attenuated.[6] In addition to these regulatory pressures and the

[4] The MU criteria in Stage 1 included (1) use of certified EHR in a meaningful manner (e.g., e-prescribing), (2) use of certified EHR technology for electronic exchange of health information to improve quality of health care, and (3) use of certified EHR technology to submit clinical quality measures (CQM) and other such measures. MU Stage 3 began after our study time frame; therefore, it is not relevant.

[5] https://www.athenahealth.com/knowledge-hub/value-based-care/what-is-meaningful-use/medicare-stage-2.

[6] Even though the push toward EMR interoperability has existed since at least the late 1980s (Dixon et al., 2020) and has improved over the years, many hospitals still have not achieved interoperability (Dixon et al., 2020; Furukawa et al., 2014). Also, it is important to note that industry-wide interoperability initiatives like CommonWell Health Alliance, https://www.commonwellalliance.org/about/ (designed with the intent of delivering interoperability between all EMRs, irrespective of vendor) and vendor-specific health information exchanges like Epic's *Share Everywhere* and

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corresponding standardization in supplier technologies, hospital IT professionals and consultants are accruing experience with EMR components over time and automated integration software is improving.[7] This experience should lead to a greater ability to integrate components across suppliers, especially as new EMR components replace legacy components, which would ease interoperability challenges. At the same time, the rapid push to adopt EMRs in anticipation of the MU requirements created a buying spree (i.e., to take advantage of the financial incentives), in which entire SS EMR systems were often chosen to replace stand-alone, legacy components (Angst et al., 2017b). This made the task of integrating a single, favored component (e.g., a CPOE) into the newly installed EMR base product much less resource intensive and also provided substantial interoperability benefits, but also created greater homogeneity across hospitals in terms of their EMR sourcing.

In sum, our expectation is that over our observation period, which importantly includes the 2009 HITECH enactment, and the MU criteria that are so central to EMR use, the interoperability challenges associated with intercomponent misalignment due to MS has lessened, and at the same time, the competitive advantages of SS, present in the early years, have diminished over time. Thus, we hypothesize:

> Hypothesis 2: The relationship between moving closer to single-sourcing and conformance quality will be negatively moderated over time.

4 | RESEARCH METHODS

Our panel includes hospitals that operated continuously from 2006 to 2013. Yearly data of the number of hospitals range from 1321 in 2006 to a maximum of 3278 in 2013.[8] Data were obtained from: (1) HIMSS Analytics, which provided data on which EMR components hospitals adopted,[9] the suppliers who provided the components, and when the component was purchased; (2) HospitalCompare, which provided data on our CQ measure; and (3) CMS Public Use Files (PUF) where additional hospital data were required.

4.1 | EMR software suites

EMRs are complex multicomponent software suites that manage patients' medical records at health care delivery organizations. EMRs are modular software systems in the sense that hospitals can adopt a subset or all of the components in a suite and can source individual components within a suite from a portfolio of suppliers, contingent upon their receptiveness/aversion to integration/interoperability issues described above. Consistent with past research (Adler-Milstein et al., 2014; Angst et al., 2017b; Furukawa et al., 2010; Sharma et al., 2016), the components used in our analysis are considered *clinical health IT* or *augmented clinical health IT* and include: Clinical Data Repository (CDR), Clinical Decision Support System (CDSS), Computerized Practitioner Order Entry (CPOE), Electronic Medication Administration Record (EMAR), Nursing Documentation, Order Entry (including order communication), Physician Documentation.[10] These components are designed to improve patient care and provide decision support functionality, both of which may impact CQ.

4.2 | Calculating change in closeness to single-sourcing

To examine a hospital's sourcing strategy, we used sequence analysis (Angst et al., 2011; Angst et al., 2017b), which has become increasingly more popular in the social sciences as it allow scholars to investigate a variety of research questions (Angst et al., 2011; Angst et al., 2017b). Using sequence analysis allows for richer insight in regard to where a hospital falls on the sourcing continuum than a discrete count of the number of suppliers used in an EMR suite; see Online Appendix C for a detailed example. We leverage a novel method introduced by Angst et al. (2017b), which allows us to use a continuous measure of closeness to SS without having to create discrete clusters, sourcing strategy categories, or simple counts, all of which fail to capture the complexity of the context. We included both commercially developed components as well as internally developed components in our main analysis to capture a comprehensive understanding of the EMR landscape. Following Angst et al. (2017b), we began by creating a "target" sourcing sequence that represents a prototypical SS configuration (see Online Appendix C for additional details on how the sequences were coded). This allows us to calculate a numeric distance between each hospital's actual sourcing configuration and the "target" sourcing sequence.

After constructing the sequences, we quantitatively compare pairwise sets of sourcing sequences using an algorithm known as a generalized Levenshtein distance (Levenshtein, 1966) in the statistical program R (R Core Team, 2016); see Online Appendix C for additional details. This is an appropriate approach for measuring sequence similarity (Spaulding et al., 2013). Next, we create a distance measure (scaled from

Care Everywhere, https://en.wikipedia.org/wiki/Epic_Systems (designed to link only providers with Epic systems), were in nascent stages during the timeframe of our study so their effects were just beginning to materialize.

[7] https://info.harmonyhit.com/acton/attachment/18236/f-0008/1/-/-/-/-/HDA-CaseStudy-Torrance-Health-Association.pdf.

[8] Once a hospital adopted five or more EMR components, it was included in our sample; this was to ensure that we were truly capturing a hospital's sourcing strategy. For example, it is not possible to define a sourcing *strategy* when a hospital has only adopted one or two EMR components.

[9] We consider EMR component *adoption* rather than *use* for several reasons: (1) adoption is a well-established focal variable in the literature (e.g., Sharma et al., 2016); (2) use is endogenous to adoption (i.e., one must adopt in order to use); (3) adoption is an adminstrative decision whereas use is not; and (4) estimates with adoption will be more conservative than estimates with use. Furthermore, use cannot easily be measured across the many hospitals for which we have data.

[10] See Table B1 in Online Appendix B for a definition of each component.

0 to 1 by dividing by the number of components in place during a given year) from the focal sequence to the "target" sequence. A distance measure of 1 indicates a perfect match with a prototypical SS sequence. These distance values represent closeness to SS. We then use these closeness to SS values to calculate the starting point of closeness to SS and the *change* toward or away from SS for each hospital in a given year. We take this approach so hospitals beginning with a configuration that is already a prototypical SS, or close to it, will not be penalized in the empirical specification.

Additionally, the closeness to SS variable itself is a lagged variable, where the reported values for year t are the defined value of closeness to SS for year $t - 1$. This lag allows for an appropriate amount of time for the installed component to potentially impact the outcome in a more time-appropriate way. An issue is that there is not a standard benchmark for the yearly data collected for the performance measure and closeness to SS. Thus, using the previous year ensures that our independent variable occurs before our outcome variable. It is a more causally appropriate timing (i.e., time precedence) than, for example, using closeness to SS that occurs after the measure of performance.

4.3 | Conformance quality

Conformance quality[11] represents a caregiver's adherence to evidence-based standards of care during health care delivery (Senot et al., 2016; Sharma et al., 2016). More specifically, it is a collection of core process of care measures that report the proportion of eligible patients who receive care in accordance with these guidelines or standards. It has been shown that if caregivers follow these guidelines, patient health is improved (Chassin et al., 2010). The measures were developed in 2003 by CMS for common and serious health conditions. Consistent with past scholarship (Senot et al., 2016), we consider process of care measures for three health conditions: acute myocardial infarction (AMI), heart failure (HF), and pneumonia (PN), as these measures "accurately capture whether the evidence-based care has been delivered" (Chassin et al., 2010, p. 685). Conformance quality data was collected from CMS's HospitalCompare website (see Appendix A for a complete list of the 11 individual items representing CQ that were used in this study). For CQ, we take the mean of the observed items. Thus, if a hospital were missing some of the items, the mean of the other values was used. This is reasonable due to all of the measures being on the same scale (i.e., percentage of adherence).

4.4 | Moderator and control variables

To test hypothesis 2, we used a linear time trend (i.e., years since the first year in our observation period) to model the change in CQ over time. We believe this is a conservative approach and appropriate for our context because multiple regulations (e.g., HITECH Act of 2009,[12] Affordable Care Act of 2010) took place during our observation period and hospitals could comply with these regulations at different times. The general trend over time is consistent with the use of a linear time trend to model the straight-line change generally exhibited.

Several control variables are also included in our model to account for their potential influence on CQ and to control for differences among the hospitals (i.e., to reduce the potential that important omitted confounders are responsible for the relationships). *Log of hospital size* (number of staffed beds) and *log of system size* (number of hospitals in the focal hospital's system) are included to control for scale effects of hospital size, both of which change over time. Use of the natural log smooths the effects of outliers and reduces skewness in both variables. We include *case mix index*, which captures "the clinical complexity" of procedures (Peng et al., 2020, p. 503) and severity of complications within a given hospital, to control for hospital variations in processes and routines, which also changes over time. *Number of components adopted* in a given year is included to isolate the EMR adoption effects from the EMR sourcing strategy effects with which we are most interested. We also include three binary control variables to reflect whether the hospital is *for profit* or *not-for-profit*, *academic* or *nonacademic*, and *faith-based* or not, all of which can theoretically change over time, though faith-based and not-for-profit do not change. The variable *primary supplier strength* is used to control for the market power of the most frequently used EMR component supplier for each hospital. This measure of strength is calculated as the proportion of times in a given year a particular supplier was used across all hospitals and is based on the EMR market share for each supplier. *Degree of switching* was included to control for the number of supplier switches that took place for EMR components in any given year.[13] This measure is a summation of the total number of changes (switches) that occur for each hospital in a given year for commercially available components that were adopted and were switched to another commercial supplier. Values range from 0 (i.e., no switching) to 7 (i.e., a hospital switched commercial suppliers for each EMR component adopted).

4.5 | Model specification and justification

To test our hypotheses, we utilize a within- and between-specification in a mixed-effects modeling framework, which is also termed a multilevel or hierarchical model in some literatures. Below, we show the equations using a multilevel

[11] CQ is sometimes referred to as "clinical quality" in the literature (Chandrasekaran et al., 2012).

[12] We also re-ran our analysis including a HITECH dummy as a control variable. We are happy to report the results, which are available upon request, are consistent with our main findings.

[13] Our outcome measure begins in 2006, but we use 2005 data to calculate the degree of switching for the 2006 measure. Thus, switching at time t is the number of switches as measured from time $t - 1$.

framing where the mixed part of the model is in terms of including fixed effects and random (or unique) effects. The mixed-effects model statistically accounts for the nested structure of the data, in which multiple observations (over time) are nested within hospital (McNeish & Kelley, 2019; Pinheiro & Bates, 2006; Singer & Willett, 2003). This modeling framework allows for more nuanced insights into the relationships of interest (McNeish & Kelley, 2019). Specifically, our within-between approach controls for a hospital's closeness to SS at the entry or starting point of the hospital into the study (i.e., when the hospital had at least five modules adopted) and examines how a *change* closer to or away from SS relative to the starting point (the within value) impacts CQ. The literature suggests that between-relationships may differ in strength and/or direction from within- relationships (Certo et al., 2017) and "failing to recognize the important distinction between these effects can result in consequential errors in inference" (Curran & Bauer, 2011, p. 587). In particular, it is important to deconflate the variance of CQ into the between part (i.e., the starting point across hospitals) and the within part (i.e., the change a hospital experiences). Consequently, distinguishing between within- and between-relationships provides methodological rigor and a model that explicitly maps onto our research questions (Certo et al., 2017; McNeish & Kelley, 2019).

This specific model presented here is for a straight-line change model with random intercepts (starting point) and random slopes:

$$CQ_{it} = \pi_{0i} + \pi_{1i} Years_{it} + e_{it} \quad (Level\,1,\ time\,varying),$$

$$\pi_{0i} = \beta_{00} + r_{0i}\ (Level\,2a),$$

$$\pi_{1i} = \beta_{01} + r_{1i}\ (Level\,2b),$$

where i is the hospital and t is the years since 2006 = 0,1, 2,….,7. There is a correlation matrix for the random effects and a variance for the error, e, which is assumed to be homogeneous across time (i.e., homogeneity of variance). The correlation of the random effects allows one to ask questions about the correlation of change and initial status (e.g., do hospitals that start higher change less?). Notice that the intercept, π_{0i}, and the slope, π_{1i}, have i subscripts, signifying that each hospital can start at a unique value of CQ in year 2006 and can change at different rates.

Substituting the hospital-specific effects (Level 2) into the Level 1 model, we have

$$CQ_{it} = (\beta_{00} + r_{0i}) + (\beta_{01} + r_{1i})\, Years_{it} + e_{it},$$

where the first term in parentheses, $(\beta_{00} + r_{0i})$, is the intercept and the second term in parentheses, $(\beta_{01} + r_{1i})$, is the slope. These two parenthetical values consist of an overall fixed effect that represents the expected value of CQ across all hospitals (β_{00}) when $Years_{it} = 0$ and the expected change in CQ (β_{01}) for each year in the study. We purposefully use "*year since 2006*" as the time scaling for ease of interpretation of the intercept. By including random effects for the intercept, r_{0i}, and slope, r_{1i}, our model allows for a different starting point on CQ at the start of the study and a different change on CQ over time. This mixed-effects model is appropriate given the nesting structure of our data and the absence of a selection criteria for hospitals to be included (e.g., we selected all hospitals in the United States for which data were available, not a subset based on some criteria such as "top 100 hospitals"). As we include controls, covariates, and concomitant variables that may be important factors in CQ over time, we specify all of these variables as time varying covariates. Including these J variables, which may be important for CQ, but are not relevant to our theoretical arguments, we have:

$$CQ_{it} = \pi_{0i} + \pi_{1i} Years_{it} + \sum_{j=1}^{J} \pi_j X_{it} + e_{it},$$

which we express generically, but in the model each X_{it} represents a control variable for the ith hospital at the tth time point (we have 9 such variables). All of the controls and concomitant variables can theoretically vary over time, so they have a t subscript. We do not use a random effect for the controls or concomitant variables and, thus, there is no "i" subscript (the effect is specified to be the same for all hospitals; they are fixed effects in the mixed-effects framework).

Next, we include the independent variable of interest (i.e., CSS) in a within-between approach that explicitly partitions the variance of CSS into a within part and a between part. Using $\overline{\overline{CSS_i}}$ to denote the starting point for CSS upon entry into the study (i.e., once five or more components of the EMR have been adopted) for the ith hospital and, thus, $CSS_{it} - \overline{\overline{CSS_i}}$ denoting the within hospital change since entry, we have:

$$\begin{aligned} CQ_{it} &= (\beta_{00} + r_{0i}) + (\beta_{01} + r_{1i})\, Years_{it} + \sum_{j=1}^{J} \pi_j X_{it} \\ &+ \beta_{0(J+1)} \overline{\overline{CSS_i}} + \pi_{(J+2)} \left(CSS_{it} - \overline{\overline{CSS_i}} \right) + e_{it}. \end{aligned}$$

Notice above that $\overline{\overline{CSS_i}}$ has a β coefficient denoting a between variable, whereas $CSS_{it} - \overline{\overline{CSS_i}}$ has a π coefficient denoting a level 1 variable.

4.6 | Analysis and results

Table 1 displays descriptive statistics and correlations. For our mixed-effects models, we used full information

TABLE 1 Descriptive statistics and correlations

		Mean (SD)	Max, Min	1	2	3	4	5	6	7	8	9	10	11
1	*Conformance quality*	96.66 (4.42)	100, 37.0	1.00										
2	*Hospital size*[15a]	5.19 (0.77)	7.35, 2.56	0.12**	1.00									
3	*System size*[15a, 16b]	1.99 (1.67)	5.08, 0.00	0.32**	–0.03	1.00								
4	*Case mix index*[16b]	1.50 (0.25)	2.54, 0.84	0.16**	0.70**	0.09**	1.00							
5	*Primary supplier strength*[16b]	0.14 (0.06)	0.23, 0.00	0.04	–0.11**	0.12**	–0.11**	1.00						
6	*Degree of switching*[16b]	0.63 (1.19)	7.0, 0.0	0.005	0.04	0.07**	0.05*	–0.17**	1.00					
7	*Components adopted*	0.26 (0.72)	6.0, 0.0	–0.002	–0.07**	0.04*	–0.05*	0.05*	0.10**	1.00				
8	*For profit*	0.30 (0.46)	1.0, 0.0	0.02	–0.08**	0.26**	–0.08**	0.11**	–0.06**	0.02	1.00			
9	*Academic*	0.07 (0.26)	1.0, 0.0	–0.02	0.41**	–0.10**	0.38**	–0.18**	0.08**	–0.06**	–0.04	1.00		
10	*Faith based*	0.24 (0.43)	1.0, 0.0	0.05*	0.12**	0.20**	0.15**	0.00	0.09**	–0.01	–0.27**	–0.04*	1.00	
11	*CSS (starting)*[b]	0.81 (0.24)	1.0, 0.0	–0.07**	–0.04*	–0.18**	–0.09**	0.32**	–0.16**	–0.01	0.01	–0.04	–0.05*	1.00
12	*CSS (change)*[b]	0.08 (0.26)	1.00, –0.83	0.00	0.02	0.07**	0.07**	–0.04	–0.21**	–0.04	–0.06**	–0.03	–0.01	–0.61**

Note: Descriptive statistics for 2013 using all available data for each individual variable for the mean, SD, Min, and Max with listwise deletion used for the correlation matrix (listwise n = 2149). Descriptive statistics for other years are available upon request. * $p \langle 0.05$[a] These variables are log transformed.
b. These variables are lagged.

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TABLE 2 Within-between hospital mixed-effects results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	94.287***	89.975***	84.235***	84.046***	84.478***	84.162***	83.505***
	(0.078)	(0.126)	(0.471)	(0.536)	(0.627)	(0.535)	(0.638)
Years since 2006		1.104***	1.008***	0.999***	0.900***	1.029***	1.185***
		(0.023)	(0.023)	(0.023)	(0.078)	(0.024)	(0.086)
Log(*hospital size*)			0.659***	0.656***	0.656***	0.661***	0.660***
			(0.101)	(0.101)	(0.101)	(0.101)	(0.101)
Log(*system size*)			0.537***	0.535***	0.534***	0.530***	0.531***
			(0.038)	(0.039)	(0.039)	(0.039)	(0.039)
Case mix index			1.651***	1.616***	1.616***	1.641***	1.643***
			(0.292)	(0.293)	(0.293)	(0.293)	(0.292)
Primary supplier strength			1.849**	1.637**	1.712**	2.102***	2.031***
			(0.732)	(0.758)	(0.760)	(0.759)	(0.760)
Degree of switching			–0.109***	–0.058*	–0.056*	–0.071**	–0.075**
			(0.030)	(0.032)	(0.032)	(0.032)	(0.032)
Components adopted			–0.536***	–0.522***	–0.522***	–0.503***	–0.501***
			(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
For profit			–0.798***	–0.770***	–0.770***	–0.778***	–0.780***
			(0.148)	(0.149)	(0.149)	(0.149)	(0.149)
Academic			–0.753***	–0.755***	–0.752***	–0.717***	–0.718***
			(0.211)	(0.211)	(0.211)	(0.211)	(0.211)
Faith based			–0.226	–0.217	–0.215	–0.213	–0.214
			(0.156)	(0.157)	(0.157)	(0.157)	(0.156)
CSS starting				0.292	–0.258	–0.133	0.678
				(0.301)	(0.512)	(0.305)	(0.526)
CSS change				0.917***	0.980***	3.575***	3.725***
				(0.223)	(0.228)	(0.392)	(0.400)
Years since 2006 × CSS starting					0.121		–0.187*
					(0.091)		(0.099)
Years since 2006 × CSS change						–0.638***	–0.697***
						(0.078)	(0.084)
Observations	17,563	17,563	16,533	16,526	16,526	16,526	16,526
Log likelihood	–54579.490	–50974.820	–46080.570	–46054.800	–46053.920	–46021.260	–46019.470
Akaike inf. crit.	109165.000	101961.600	92191.140	92143.600	92143.840	92078.510	92076.940
Bayesian inf. crit.	109188.300	102008.300	92306.840	92274.720	92282.670	92217.340	92223.480

Note: Standard errors in parentheses.
+$p < 0.10$.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

maximum likelihood, with implementation of the model being done with R (R Core Team, 2016) using the lme4 package. The results from our analysis are shown in Table 2. Although "endogeneity is not a problem that can be solved" (Ketokivi & McIntosh, 2017, p. 7), our within-between approach explicitly addresses hospital-level (i.e., Level 2) endogeneity issues (McNeish & Kelley, 2019) in a way analogous to a traditional fixed-effects econometric approach. Also, our use of longitudinal data offers "advantages of addressing endogeneity" (Lu et al., 2018, p. 54) by "eliminating at least some of the effects of one of the leading causes of endogeneity, unobserved heterogeneity" (Ketokivi & McIntosh, 2017, p. 7). In robustness checks, we further address endogeneity concerns by using a traditional econometric approach and a fixed-effects panel instrumental variable (IV) regression, which is a well-established approach in the OM literature.

We begin our discussion with Model 3 (Table 2), which is the baseline condition prior to inclusion of the variables of interest. Here, we show the coefficients and statistical significance of our set of control variables and the intercept. All coefficients can be interpreted directly as their expected contribution to CQ (i.e., percentage of time clinical quality guidelines are followed), holding everything else in the model constant. In Model 4 (Table 2), we control for a hospital's closeness to SS starting point (between), while examining a hospital's change in closeness to SS (within) to evaluate our hypotheses. In doing so, we see that closeness to SS (within) has a positive and statistically significant effect on CQ (0.917, $p < 0.001$). The coefficients for a change in closeness to SS (within) show that an individual hospital moving 0.5 units closer to SS will have a predicted CQ score that is 0.4585 ($= 0.5 \times 0.917$) units higher in the future than its CQ score in the past, holding everything else constant. As such, we find support for Hypothesis 1b, but not Hypothesis 1a.

We also examine how time impacts the change in closeness to SS-CQ relationship. Model 6 (Table 2) is our model of interest because it includes the interaction between change in closeness to SS (within) and *years since 2006*, rather than also the interaction between closeness to SS (between) and *years since 2006*. As noted above, we control for hospitals' closeness to SS at the starting point of entry into the study (the between-hospital value), and, thus, only hypothesize how hospitals change from their starting point toward or away from SS (the within value) impacts CQ. As shown in Model 6, the interaction of interest (*years since 2006* × *CSS change*) has a negative and significant effect on CQ (–0.638, $p < 0.001$), which suggests that the positive effect that a change in closeness to SS has on CQ is reduced over time. This result also holds in Model 7 (Table 2), which we include for completeness and to demonstrate the robustness of our results. In sum, our findings offer support for Hypothesis 2.[17]

4.7 | Robustness checks

We conducted several additional analyses to assess the robustness of our results. First, we reran our analysis with five components instead of the seven components in our main analysis.[18] Second, we reran our analysis with ten components—the seven in our main analysis along with Laboratory, Pharmacy System, and Radiology IS, which fall into the category of augmented clinical IT (Sharma et al., 2016). Third, we removed internally developed components and reran our analysis using only commercially sourced components.[19] Fourth, we conduct a fixed-effects panel IV regression analysis, which is a common approach to address endogeneity concerns (Ketokivi & McIntosh, 2017; Lu et al., 2018). See Online Appendix E for detailed information on each analysis and associated results, all of which are consistent with our main findings.

5 | DISCUSSION AND CONCLUSION

There has been a dramatic shift in the role that IT plays in not only a firm's operations, but also its overall strategy. While there is a growing literature investigating the performance implications of adopting IT, equally important questions remain with respect to *how* a firm's suite of IT resources should be sourced, implemented, and managed (Ross & Weill, 2011; Van de Vrande, 2013). Our study contributes toward addressing the need for a more fine-grained approach by examining an extremely important aspect of health IT that has been largely overlooked: the sourcing of hospital EMRs (Agarwal et al., 2010).

To help ground our research in practice and better understand the implications for decision-makers in the field, we interviewed six key informants who have extensive experience in requirements analysis, technology selection, implementation, after-sales service, and actual use of EMR software (see Table 3). The key informants were strategically selected so we could capture insights about EMR sourcing, selection, and integration as well as draw from the physician's perspective about EMR ease of use and interoperability issues present with different sourcing strategies and how these issues changed over time.

Each interview lasted 45–60 min, which is consistent with other research that leverages interviews (Levina & Su, 2008). Two or more members from the research team participated in each interview, which enabled one researcher to primarily focus on taking notes while other members of the research team focused on asking follow-up questions and guiding the interview. The semistructured interviews were guided with open-ended questions, but key informants were allowed and encouraged to discuss any factors that may be relevant to our study. To establish trust, at the beginning of each interview, we assured anonymity and only provided a brief overview of the study, which helps avoid "priming respondents to answer in particular socially acceptable ways" (Steenkamp et al., 2010, p. 1–2).

As noted above, the objective of conducting these interviews was to better position our results in the context of the EMR landscape that existed between 2006 and 2013. This was a dynamic time period where regulatory policies, technology, and competition were rapidly changing. Our hope

[17] See Figure D1 in Online Appendix D for a plot of the interaction effect.

[18] We included the following components: CDR, CDSS, CPOE, Physician Documentation, and Order Entry as they are well-established in the literature as constituting an "advanced" EMR (Angst et al., 2017b).

[19] Internally developed components could be designed to minimize both organization-IT misalignment and intercomponent misalignment and, thus, including them in our analysis might underestimate the performance difference between SS and MS configurations.

TABLE 3 Information on key informants

Key informants	Experience
Key Informant #1	10 years of experience at a major health care IT (HIT) company (EMR Vendor#1), which included time focused on implementing EMR systems at hospitals nationwide. Extensive experience as a senior executive (Executive VP) at multiple firms (Firm#1, Firm#2) focused on providing consulting services for health care organizations selecting and/or implementing EMRs and auxiliary systems.
Key Informant #2	7 years of experience at a major HIT company (EMR Vendor#1), which included time focused on selecting and implementing EMR systems. Currently a practicing physician who is also a senior executive (Chief Medical Officer) at an organization that provides consulting services for health care organizations selecting and/or implementing EMRs (Firm#1).
Key Informant #3	8 years of experience at a major HIT company (EMR Vendor#2). Currently an IT project manager specializing in ambulatory settings; also has extensive experience selecting and implementing EMRs.
Key Informant #4	15 years of experience at a major HIT company (EMR Vendor#1). Currently, a senior executive (Associate Director of Electronic Health Records) focused on EMR collaborations at a majority health care organization (EMR-Partner Firm).
Key Informant #5	7 years of experience as a senior executive (Chief Information Officer) of a major health system that consists of several hospitals across multiple states (EMR Vendor#2 User).
Key Informant #6	A practicing physician who has also held a senior leadership position (Chief Medical Information Officer) in a major health system (EMR Vendor#2 User) for 10 years.

At the request of the interviewees, all names and institutions were masked. The roles may not represent a complete list of interviewees' titles and the order in which roles are listed may or may not coincide with the order in which the interviewee assumed the roles. Interview questions available upon request.

was that our key informants could add color to our findings and either reinforce or challenge our empirical results. Not only did the interviews accomplish that goal, but they also provided rich insights into things that the data did not reveal. This helped us tease out the unique implications of our study, gather insights about how our findings might guide managerial decision-making, shed light on how new regulations influence hospital sourcing strategies, and inform future research. When discussing the implications and contributions of our research, we consider key gaps in the literature that our study helps fill, but also leverage these rich insights obtained during the interviews. This approach enabled us to identify a wide variety of contributions that may not have been revealed otherwise. Instead of partitioning the implications of our research toward specific audiences (e.g., academics, practitioners, etc.), we structure our discussion around key themes, and within each theme, we talk about how it informs research, managerial decision-making, and policy decisions.

5.1 | The impact of EMR sourcing strategy

Our study demonstrates that *how*, not just *if*, EMRs are implemented is consequential to CQ, which can increase a hospital's reimbursements (Sharma et al., 2016). The implication is that administrators cannot assume that the adoption of health IT alone is sufficient to realize the full performance benefits associated with the technology. Instead, they must also consider how the number of different suppliers included in the sourcing portfolio affects routines, interoperability, and ultimately, CQ. Aligning the sourcing strategy with technical and operational considerations is likely to result in superior patient outcomes. In addition, the effect size we find has practical significance (moving 0.5 units closer to SS increases the CQ score by 0.46 units, which means that nearly 0.5% more individuals are receiving appropriate care), and compliance with clinical quality guidelines is notoriously difficult to improve (Chassin et al., 2010). To put this number into perspective, during the timeframe of our study, US hospitals admitted approximately 35 million patients per year. All else being equal, if hospitals were 0.5 units closer to SS in a given year, approximately 175,000 more patients per year would have received evidence-based care.

5.2 | Evolution of interoperability

A driving factor of superior performance with the SS approach is interoperability considerations between components. Early in our observation period, pursuing a SS strategy translated into better performance by minimizing the misalignment between the multiple software components comprising the EMR system. By minimizing intercomponent misalignment, the EMR system's interoperability improves, which corresponds with greater clinician visibility, a lesser need for manual data entry, fewer medical errors, and increased speed of care (Brailer, 2005; Tierney et al., 2013), all of which was validated by key informant #6. However, over the time period of our study, the comparative benefits of SS relative to MS lessened. We assumed that this finding was due, in part, to regulatory incentives (e.g., the HITECH Act) motivating the health IT community to work toward greater standardization in data coding and communication protocols, which would result in improved interoperability across EMR supplier technologies (Adler-Milstein & Jha, 2013; Blumenthal, 2010). Key informants #1 and #5 validated these assumptions and also revealed more nuanced insights.

During our interviews, key informant #5 noted that the interoperability issues prevalent in the latter years of our observation period can also be attributed to how each EMR supplier defines key health care concepts and data fields. Key informant #2 specifically discussed how something as simple as an allergy is defined and coded differently by EMR suppliers, and that this difference is reflected in the fact that disparate EMR components cannot communicate with each other. They also elaborated that the technology used to "translate" the definitions from one EMR component sourced from one supplier to another EMR component sourced from a different supplier is imprecise and error-prone. Key informants #3 and #4 discussed how integrating the two components relies on humans to do the translating, which can introduce errors and is extremely resource intensive as there are potentially thousands of fields that do not map appropriately. Key informant #1 noted that if a hospital is considering an MS approach, it needs to assess safety issues and additional EMR maintenance costs. Leveraging analytics methods such as AI, machine learning, and advanced text analysis could help in this effort and could make the MS strategy more desirable for hospitals in the future. This is an intriguing area for future research.

From a policy or regulatory perspective, standardization has really focused on data coding and communication protocols. For example, on March 4, 2019, CMS released a proposed rule[20] that comments to a great extent on interoperability of EMRs and the role that suppliers play in the standardized exchange of data. While such standardization on the exchange of data is critical, perhaps more can be done on standardizing key definitions across EMR suppliers, and as noted above, collaborative efforts between suppliers could result in 3rd-party data exchanges.

5.3 | Importance of adopting a longitudinal perspective

Our study also highlights the importance of using longitudinal rather than cross-sectional data. Specifically, interpreting the relationship between change in closeness to SS and CQ without considering the effect of environmental changes or important regulatory events that take place over time can lead to errors in inference. If only the data from the early years of our observation period were available, we would not have observed that the competitive benefits of approaching SS diminish over time. This finding has broad research implications in that it highlights the need to consider practice-performance relationships dynamically, rather than statically.

5.4 | Partitioning the within-between effects

The majority of past scholarship on IT sourcing has focused on a single level of analysis. Our study demonstrates the value of adopting a "within-between" specification (Certo et al., 2017; Freeman et al., 2020; Mundlak, 1978) in a mixed-effects modeling framework (Gelman & Hill, 2006; McNeish & Kelley, 2019; Singer & Willett, 2003). This approach allows us to answer questions related to not only closeness to SS, but also how hospitals' starting points (between) and change from those starting points (within) have an impact on performance. This disambiguation can be called a contextual effect (e.g., Raudenbush & Bryk, 2002, p. 139–141), where the between aspect of a relationship may not be consistent with the within aspect. Indeed, we find that context matters, as it is not where the hospital starts, but rather, how it changes that is key. While this approach is gaining traction long after Mundlak (1978) introduced it (Bell & Jones, 2015; McNeish & Kelley, 2019), it is still underutilized in operations management research, as noted by Freeman et al. (2020). Our study underscores the value of this methodological approach. Specifically, it reveals more nuanced insights, while considering the nesting structure inherent in the data and the idea of fixed and random effects in a single model. An important practical implication to managers is that this approach can provide more actionable insights, as hospitals have less control over their sourcing starting position, but they completely control their sourcing approach over time.

5.5 | The evolution of enterprise IS sourcing strategies over time

While the context of EMR sourcing is specific to health care, the environmental dynamics experienced are relevant to a variety of different enterprise information systems. Customer relationship management (CRM) systems, for example, are currently undergoing a similar transformative era in which vendors such as Salesforce.com are attempting to be the backbone infrastructure on which application-specific components—from Salesforce or from 3rd parties—are added. For this to be successful, interoperability is key. Just as EMRs were conceptualized as individual components that fit together to comprise EMR suites in the early years, CRMs are evolving into modular systems. MS was popular because hospitals could pick the best component for each unit or function within the hospital. Hospitals quickly realized that hospital-wide performance was not maximized by the functions of each component, but rather how the entire system worked together, which drove the migration to SS (Angst et al., 2017b). Yet, we also know that SS will provide early benefits but they will be short-lived as more firms pursue that strategy. Policymakers should recognize the power they wield as it relates to encouraging adoption, but also be cautious that regulations can stymie innovation. Standardization has benefits, but at the expense of differentiation.

5.6 | EMRs in the future

Questions about EMR sourcing strategies are likely to remain into the foreseeable future, but it will be interesting to follow its evolution because, at least according to key informants #1 and #6, there is a new shift in thinking surrounding what an EMR is. They talked about EMRs becoming *platforms*, where the core of the EMR is simply a software application that acts as an interface between components that facilitates transactions. In a situation like this, the platform would provide the rules/governance/architecture and it would be a 3rd-party

[20] https://www.federalregister.gov/documents/2019/03/04/2019-02200/medicare-and-medicaid-programs-patient-protection-and-affordable-care-act-interoperability-and

supplier's role to seamlessly fit into the EMR,s architecture such that it is literally plug-and-play. Key informants #2, #3, and #4 also suggested that the EMR of the future would be a "hub," and that the entire structure would be built to support the revenue cycle of a health care provider. This is intriguing considering that the EMR was initially conceptualized and designed as a clinical software tool. Future research conceptualizing an EMR as a key component of the revenue cycle rather than a clinical tool could have major implications for hospitals and patients alike.

5.7 | Limitations and future research

Notwithstanding the important contributions this study makes to theory and practice, there are several opportunities for future research. Our study spans 2006 to 2013, which was a dynamic period in the health care industry as it relates to EMR adoption. It also allowed us to study EMR adoption before it was mandated. Future research could extend our study to include more recent data. Future research that examines other moderators of the sourcing strategy-performance relationship could also provide fruitful insights. For example, service variety influences information processing needs (Peng et al., 2020) and, therefore, may affect the SS versus MS tradeoff. Additionally, mergers and acquisitions often result in IT switching for hospitals, which can cause a decrease—at least temporarily—in CQ following mergers. Senior leadership may influence a hospital's IT sourcing strategy and, thus, future research that investigates the impact of changes in senior leadership or reporting structures would be insightful. Lastly, there are other important dimensions to health IT implementation (e.g., workflow redesign, training and development, etc.) that should be identified and evaluated to continue advancing our knowledge of the relationship between EMR implementation and hospital performance. We hope our study helps lay the foundation for future research on the relationship between health IT sourcing decisions and hospital performance. Given that hospital performance often means life or death for patients, this is a particularly important area that warrants future research.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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