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The Impact of Information Technology and Communication on Medical Malpractice Lawsuits

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Health care organizations have substantially invested in Health Information Technology (HIT) as part of an effort to improve quality. However, many hospitals fail to generate positive returns on this significant investment, based on reimbursements for quality measures through the Affordable Care Act (ACA). Given the high cost of lawsuits, we investigate if HIT adoption reduces lawsuits, and their attendant costs, as another consideration in HIT payoffs. We use operational transparency theory to develop hypotheses on the individual and joint impact of HIT and communication quality in influencing patients' likelihood to file a lawsuit. We combine data on 168 hospitals in the state of Florida from 2007 to 2011 in order to investigate these relationships. Analysis using a fractional response model indicates that HIT has a direct impact in reducing the number of lawsuits, this effect being higher for hospitals with higher communication quality scores. These results remain consistent irrespective of the type of caregiver (physician vs nurse) communicating with the patient or the severity of injury resulting in the lawsuit. Our results also remain robust under different operationalization of key independent variables and alternate model specifications. These results provide a better understanding of the mechanisms that reduce lawsuits.

Key words: malpractice lawsuits; health information technology; communication quality; healthcare delivery; fractional response model
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1. Introduction

Health care organizations have substantially invested in Health Information Technology (HIT) (Henry et al. 2016). While investment sums vary by organization strategy and size, estimates range from $2.7 million for a 50 bed hospital to $600 million for a 73 hospital organization (Altarum Institute 2011, Barlas 2011). Organizations have invested in HIT for multiple reasons, such as improved quality, reduced costs and rework, and increased reimbursement payments under the Affordable Care Act (ACA) (Chaudhry et al. 2006, Mangalmurti et al. 2010). Although HIT can enable quality improvements, they are not guaranteed (Jones et al. 2014, Kohli and Devaraj 2004). Further, even with quality improvements, when management considers primary outcomes, such as increased reimbursements under the ACA, return on HIT investment is far from certain (Barlas 2011). However, HIT may influence more distal outcomes that also impact costs and benefits; we investigate one such outcome: lawsuits.

Patients (and/or their families) file medical malpractice lawsuits believing patient injury resulted from care providers *failing to provide the appropriate standard of care* (Mangalmurti et al. 2010). In other words, malpractice suits result from a care delivery quality failure. These lawsuits result in significant direct costs: ~$55 billion per year in the United States (Mello et al. 2010), accounting for items like malpractice insurance, settlements, awards, defensive medicine costs, and administrative costs. Beyond the costs, malpractice suits cause further troubles: they cause stress in care providers over multiple years, thus affecting care providers' mental health and ability to focus on other patients (Mello et al. 2010, Menon and Kohli 2013, Seabury et al. 2013). Thus, lawsuits indicate a quality problem with both quantifiable and unquantifiable costs that hurt hospital operations and therefore deserves investigation.

Past research suggests that HIT could be an important driver of lawsuits (Miller and Tucker 2014, Quinn et al. 2012, Victoroff et al. 2013, Virapongse et al. 2008). However, these same studies have drawn conflicting conclusions on the efficacy of HIT. We further explore this phenomenon through econometric models by incorporating an additional factor which could impact how HIT adoption affects lawsuits: communication quality. Although HIT houses patient information that could help provide accurate process information to patients, effective communication between caregivers and patients is needed to interpret and convey this information to patients. A better understanding of process information helps improve patients' perceptions of care delivery (Buell and Norton 2011, Buell et al. 2017, 2018) and hence their likelihood to file lawsuits in case of a service failure. Thus, the quality of communication between caregivers and patients could be the missing link to resolving the inconsistent findings on the efficacy of HIT in reducing lawsuits. We investigate this link by answering the following research question: *How does HIT independently and in combination with communication quality influence the number of lawsuits filed (after controlling for the quality of care delivered at a hospital)?*

To address this research question, we collected data from 168 Florida hospitals in 2007–2011. We combined data from many different data sources: (i) Florida Office of Insurance Regulations for medical malpractice lawsuit data, (ii) hospital regional characteristics from the U.S. Census Bureau database, (iii) Healthcare Information and Management Systems (HIMSS) Analytics data for HIT, (iv) Centers for Medicare and Medicaid Services (CMS) Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) data for measuring caregiver-patient communication quality, (v) CMS cost reports and (vi) CMS process-of-care data for hospital characteristics and other controls.

Applying an instrumental variable fractional response model to our data, we find that HIT reduces the number of lawsuits filed against a hospital. We also find that this effect is contingent on the communication quality at the hospital. That is, we observe that as HIT increases, hospitals with high communication scores observe a reduction in lawsuits per year, whereas those with low communication scores observe an increase in lawsuits. We also find significant heterogeneity in this relationship based on the level of HIT. Specifically, we find larger positive synergies between HIT and medium to high levels of communication in early cycles of HIT adoption and smaller positive synergies in later cycles of HIT adoption. On the other hand, for low communication hospitals, the observed increase in lawsuits becomes stronger as the HIT adoption at a hospital increases. This result explains some inconsistent findings in the HIT–Lawsuits literature by identifying communication quality as a moderating factor. Together these results provide a better understanding behind the operational mechanisms that reduce lawsuits. These results remain consistent irrespective of the type of caregiver (physician vs nurse) communicating with the patient or the severity of injury driving the lawsuit. Additionally, our results remain robust to different model specifications, operationalization of key variables, and endogeneity concerns with our communication quality and HIT variables.

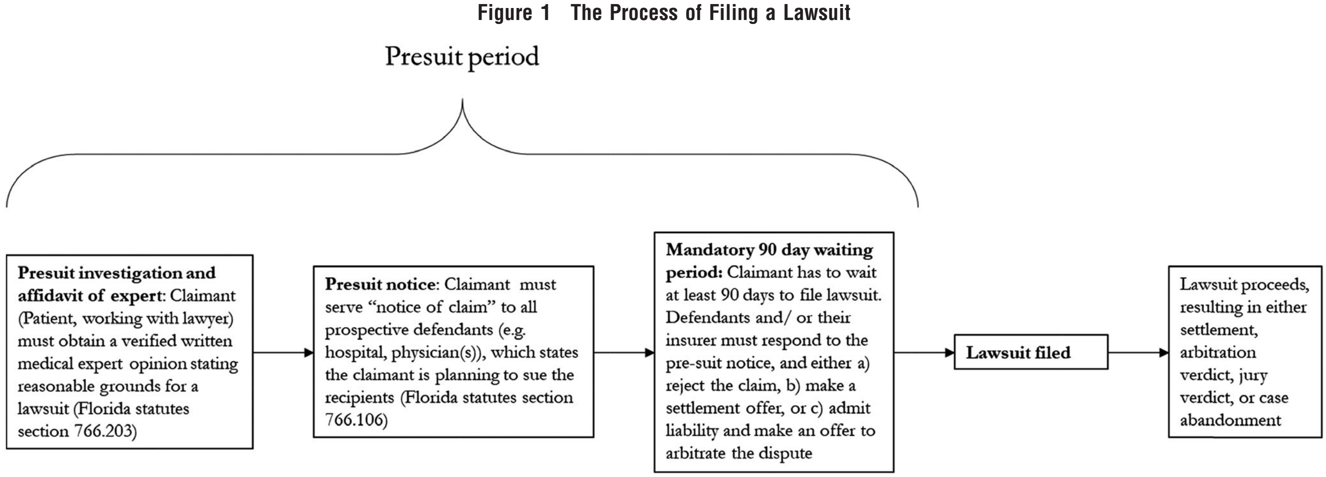
2. Background and Literature Review

2.1. Process Overview: Medical Malpractice Lawsuits

In order to analyze how managerial actions are associated with lawsuits, we first need to understand the process of pursuing a medical malpractice lawsuit. Thus, we explain the role of the hospital, patient, and lawyer in pursuing a medical malpractice lawsuit.

For a lawsuit to be viable, the case must meet four criteria (Bal 2009). First, the hospital must have a legal duty to provide care to the patient. Second, the hospital must have *failed to provide the appropriate standard of care*—that is, the care that a reasonable provider would deliver (Mangalmurti et al. 2010). Third, the failure to deliver appropriate care must have caused the injury. Fourth, the injury must have caused damages to the patient. Before a lawyer can file a lawsuit on a patient's behalf, a qualified medical expert must review the patient's medical records and agree that the appropriate standard of care was not provided. A lawyer weighs these criteria against information provided by the patient to determine the strength of a potential case. If a lawyer accepts the case, the next step is the presuit process (shown in Figure 1).

Figure 1 The Process of Filing a Lawsuit



Florida law requires all potential medical malpractice cases follow this presuit process. During that presuit period, patients and defendants (working with lawyers and insurance companies) can reach a mutual agreement to settle or arbitrate the case before a lawsuit is filed. If an agreement is not reached during the presuit period, a lawsuit is filed and due judicial process is followed until a resolution is reached—either through a settlement, arbitration verdict, jury verdict or case abandonment.

2.2. HIT in Hospitals

Administrative and clinical data represent two distinct types of information flows in hospitals. These two information flows have different data security, processing, and integration requirements which leads to the need for different HIT solutions for these disparate information flows. In addition, while administrative data is primarily used by administrative staff, clinical data is primarily used by hospital employees involved in care delivery (nurses, physicians, technicians, etc.). Further, HIT managing clinical data perform two distinct functions: (i) collection of patient data, (ii) use of stored patient data for reporting and decision support. Sharma et al. (2016) explain these differences in HIT and classify them into three bundles (clinical, augmented clinical and administrative) based on the purpose and primary users of individual HIT.

Clinical HIT are used for patient data collection, diagnosis, and treatment. These HIT variables are primarily used by technicians and, to a limited extent, by caregivers (i.e., nurses and physicians). Examples of clinical HIT include a CT scan machine and echocardiology machine. Augmented clinical HIT build on the patient data collected by clinical HIT and add integration, reporting and decision support capabilities to it. Extensive caregiver (i.e., nurse and/or physician) interaction with these HIT characterize this bundle, and hospitals have increasingly adopted these HIT due to the HITECH Act. Examples of augmented clinical HIT include a Clinical Physician Order Entry System (CPOE) and Clinical Decision Support System (CDS). Finally, administrative HIT manage the administrative data flow within the hospital and are used primarily by administrative staff. Examples of administrative HIT include payroll and benefits administration.

We study the impact of augmented clinical HIT on lawsuits, due to their ability to impact caregiver routines and their potential to reduce the lead time to access patient data (Sharma et al. 2016)—both of which can influence quality of care and operational transparency, hence lawsuits filed against the hospital. We control for the clinical and administrative HIT level of hospitals.

2.3. The Effect of HIT on Lawsuits

The literature examining how HIT impacts quality lacks clear consensus. Some authors have proposed that HIT improves the quality of care delivery through multiple mechanisms, such as decision support, improved communication between care providers and improved adherence to standardized care guidelines (Chaudhry et al. 2006, Mangalmurti et al. 2010, Queenan et al. 2011). Although those mechanisms are reasonable, an article reviewing 236 HIT-quality articles concluded that only 56% of the 236 studies (most conducted at a single, research and/or teaching hospital) show positive associations between HIT and care quality (Jones et al. 2014). A smaller set of studies investigates how HIT adoption affects quality of care across a number of different hospitals and systems, finding many positive associations but some mixed outcomes as well. On the positive side, Appari et al. (2012) show that HIT adoption leads to better adherence to medication guidelines; others provide support for HIT driving better process quality of care measures (Gardner et al. 2015, Sharma et al. 2016). On the negative side, McCullough et al. (2010) find only 2 of 6 process of care metrics are positively affected by HIT. Appari et al. (2013) found that HIT adoption up to a certain level improved quality; as hospitals continued to adopt HIT, they saw a decrease in quality outcomes. These studies use different quality measures and varying outcomes, suggesting HIT has great potential but does not guarantee positive quality outcomes.

Because medical malpractice lawsuits result from a quality failure, the HIT–lawsuit literature forms a subset of the HIT-quality literature, with medical malpractice suits as the quality metric. There is a small but growing body of work in this area. Closely related to medical malpractice lawsuits are medical malpractice premiums; Menon and Kohli (2013) show that hospitals that invest in HIT have both better future care quality and lower malpractice premiums, which are highly correlated with fewer lawsuits. Ransbotham et al. (2016) find that use of electronic medical records reduces the time to resolve medical malpractice lawsuits.

Directly related to our study, literature regarding the impact of HIT on the number of lawsuits is mixed and focused on one specific type of HIT: electronic health records. Miller and Tucker (2014), using data from hospitals across the entire United States, contend that electronic medical records (a subset of electronic health records) make medical providers more liable because electronic medical records create an electronic paper trail, and therefore, the liability that HIT creates slows down hospitals' adoption of such systems. However, once these systems are adopted, Victoroff et al. (2013) and Virapongse et al. (2008) found no association between the use of electronic health records and lawsuits. More positively, Quinn et al. (2012), found that the physicians using electronic health records had one-sixth as many malpractice claims as those that did not use electronic medical records.

We contribute to this nascent and equivocal literature stream by developing an econometrically sound estimate of the impact of HIT on lawsuits, including addressing endogeneity, an outstanding issue in the existing literature (Quinn et al. 2012, Victoroff et al. 2013). Not only does our instrumental variable approach mitigate the endogeneity concern, but we also provide multiple robustness analyses, thereby increasing the rigor of the work.

Additionally, we extend the existing HIT-lawsuit literature by expanding the scope of HIT examined. That is, we analyze the collection of augmented clinical HIT (Sharma et al. 2016), which includes electronic health records (the sole focus of most of the existing HIT-lawsuits research) and adds other integration, reporting, and decision support systems. The inclusion of this bundle of systems in our analysis is important because, as we explain in our hypothesis development, HIT can reduce lawsuits through both reducing the cognitive load and through providing a centralized location to share real-time information—which improves quality of care and operational transparency. By including in our analysis the entire suite of HIT that care providers use, we are encompassing the collection of tools that allows both reduction of cognitive load and a centralized location for relevant information.

2.4. The Effect of Communication on Lawsuits

Although the direct connection between HIT and lawsuits is important, the environment where the HIT exists impacts this relationship as well. Previous research established that better provider–patient communication leads to better patient outcomes, and provider communication quality is commonly used as a quality measure (Levinson et al. 2010, Senot et al. 2015, Stewart 1995). In addition, the evidence largely supports a relationship between good provider communication and fewer lawsuits (e.g., Bhattacharyya 2005, Levinson et al. 1997, Schleiter 2009). However, these studies generally examine communication independently of technology.

While the lawsuit literature supports the positive effects of communication, and shows mixed results for the effects of HIT, to our knowledge, there is no research examining their interaction, even though HIT introduces a third party into the patient–provider conversation (Duke et al. 2013). From a broad quality perspective, there is some evidence that HIT and communication interact negatively, through reduced eye contact and attention (Ratanawongsa et al. 2016, Rathert et al. 2016, Shachak and Reis 2009). Frankel et al. (2005) provide additional insights by recording 9 primary care physicians' interactions with 54 patients before and after introducing computers into the consultation room. They found that those providers with good (poor) communication before the introduction of the computer had even better (worse) rapport with patients after. This study took place in an early cycle of computer adoption and the authors recommended further studies to understand how technology and communication impact provider–patient relationships (Frankel et al. 2005).

We extend this line of literature by examining lawsuits as an outcome variable of the interaction effect of communication and HIT. The previous research assessing HIT and communication interaction is sparse, and none examine lawsuits as a dependent variable. By considering communication in the HIT–lawsuit relationship, to the best of our knowledge, we are the first to introduce communication as a moderating factor in this relationship.

3. Hypotheses Development

We draw from two distinct literature streams to develop our hypotheses: organizational information processing theory (OIPT) (Galbraith 1977) and operational transparency (Buell and Norton 2011, Buell et al. 2017, 2018). Please note that, given our emphasis on augmented clinical HIT, we use the term "augmented clinical HIT" synonymously with "HIT" in the remainder of the manuscript.

3.1. HIT and Lawsuits

Although the literature shows mixed results of how HIT impacts quality, using organizational information processing theory (OIPT) and operational transparency, we posit HIT will lead to reduced lawsuits.

Organizational information processing theory posits that as organizations increase in complexity, they need routines and systems to share and make sense of information (Galbraith 1977). HIT can both connect different units within a hospital and help individuals to reduce errors by mitigating the cognitive load (Angst et al. 2010, Bates and Gawande 2003). HIT can help reduce the number of cognitive errors through decision support tools, structure to aid compliance with standard process of care and sharing information across different providers (Angst et al. 2012, Buntin et al. 2010, Mangalmurti et al. 2010, Queenan et al. 2011). Moreover, those benefits grow as management builds a multifunctional system, allowing for interconnectedness between specialized software and systems, and therefore, more useful information (Chaudhry et al. 2006). Because adopting HIT can improve quality of care, use of this HIT leads to fewer cases of negligent care. In turn, these reduced incidents of negligent care lead to fewer reasons for a lawsuit and thus a reduction in patients filing lawsuits.

In addition to integration of functions within the hospital, HIT can also help improve patients' access to clinical and process information through patient portals. Patient portals integrate centralized patient information housed in HIT and make it easily available to patients. Information available through portals include medications, laboratory test results, laboratory appointments, etc. The theory of operational transparency posits that when customers can observe and understand the work done on their behalf, then customers' perceptions of services improves (Buell and Norton 2011). Support has been found for this theory in food service, self-service technology, and government services (Buell and Norton 2011, Buell et al. 2017, 2018). In this particular setting, increased HIT will facilitate faster access to process and clinical information. This in turn will improve operational transparency and improve patients' perceptions of care delivery, lowering their likelihood of filing lawsuits in case of a quality failure. Thus, we propose the following hypothesis:

H1. *Higher levels of HIT are associated with fewer lawsuits.*

3.2. HIT, Communication Quality, and Lawsuits

Literature suggests the combination of HIT and communication quality can provide additional benefits beyond those provided by communication quality or HIT alone. Specifically, a HIT system can centralize disparate patient and process data. Although parts of this patient and process data are accessible to patients through portals, the complexity of the care delivery process, and technical nature of the information makes it difficult for patients to fully interpret this information. Hence, full understanding of clinical and process information may require translation and effective communication by experts—the caregivers.

Effective communication is associated with fewer lawsuits (Bhattacharyya 2005, Levinson et al. 1997, Schleiter 2009), but all forms of communication are not equal in reducing the likelihood of lawsuits. That is, Levinson et al. (1997) saw no difference between sued and non-sued physicians regarding communication about the patient's medical condition and facts about medications. However, these researchers found that non-sued physicians provided patients significantly more *process communication*—that is, statements concerning next steps and ensuring that patients understand the information conveyed—than sued physicians. In the complex hospital environment where patients receive care from multiple specialist physicians, nurses and other caregivers, and patients have, an average of 42 tests run per hospital stay (Glouberman and Mintzberg 2001, Porter 2010, Taylor 2005), HIT provides a centralized, synchronous location to make this information available to all care providers (Mate and Compton-Phillips 2014, McCullough et al. 2016). For hospitals that have built a culture where care providers communicate well with patients, this centralized information source provides caregivers with better process information to communicate to patients.

For example, a physician can meet with a patient and explain, "I know Drs. Jones and Smith met with you yesterday and recommended we run blood tests and an EKG. The results came back and they indicate that we do not need to be concerned about congestive heart failure, but your high cholesterol is still a concern. Thus, our next steps are to prescribe a drug to help reduce cholesterol." HIT provides the physician with the most current information about this patient, but much of the value of HIT relies on the caregiver sharing this information in a meaningful way with the patient. The physician conveying this information delivers operational transparency, a clear explanation of the what and why in the care process.

Providing operational transparency–details about how services are provided–improves consumers' perceptions of services (Buell and Norton 2011, Buell et al. 2018). This is illustrated in the previous example when the physician explicitly reminded the patient about the other doctors who evaluated the patient and the multiple tests conducted to check for possible conditions. We contend that the combination of a connected HIT system and high levels of communication quality enable a hospital to provide greater operational transparency, thereby reducing the probability of a patient perceiving that he/she did not receive *the appropriate standard of care*.

On the other hand, while HIT can provide operational transparency, it can also interfere with communication. Use of HIT while in a room with a patient may result in reduced eye contact, less frequent checking of patient understanding and overall decreased patient satisfaction with a given provider (Ratanawongsa et al. 2016, Rathert et al. 2016, Shachak and Reis 2009). In fact, one study shows that HIT can worsen providers' communication skills, if those providers already were prone to poor communication (Frankel et al. 2005). If the health care providers in a hospital have low levels of communication, they may provide patients low operational transparency into the care process. For example, instead of offering the statement about how the patient met with Drs. Jones and Smith and which test results are back, the physician may see that these events have occurred, but simply say to the patient, "Okay, I'm going to prescribe a drug for you to help reduce cholesterol," without the process transparency that reminds the patient what has been done and why. With limited operational transparency, the patient does not know nor appreciate what has been done to help heal him or her, and the patient may be receiving less personal contact than previously. Because both HIT and communication quality impact the perception of service quality, a high level of HIT with poor communication may negatively impact patients' perceptions of quality and propensity to file a lawsuit. In other words, with lower operational transparency, patients have a higher likelihood of believing that the hospital *failed to provide the appropriate standard of care.* Thus, we propose:

H2. *Communication quality moderates the effect of HIT on the number of lawsuits such that high levels of communication quality coupled with high HIT are associated with fewer lawsuits when compared to low levels of communication quality coupled with high HIT.*

4. Data

4.1. Data Collection

In order to test the hypotheses, we compiled a 5-year (2007–2011) panel dataset of 168 acute care hospitals (unit of analysis) from the state of Florida. We tested our hypotheses during this period because public reporting for a number of metrics, including the HCAHPS survey, were only available starting in 2006–2007. This made 2007 a logical starting point. The end point for the panel data was determined based on the time required for resolution of lawsuits: the Florida lawsuit reporting regulations necessitate that lawsuits be reported only after resolution. Thus, if a lawsuit was opened in 2011 and resolved in 2013, it would not be reported until 2013. Approximately 96% of medical lawsuits filed are resolved within 6 years (Holman et al. 2011). Therefore, by truncating our data at 2011, we expect that nearly all (~96%) medical malpractice lawsuits filed in 2011 and a higher percentage for prior years were resolved (and therefore reported) by the time we gathered our data.

We arrived at this dataset through multiple steps. First, we combined data from different secondary sources for the analysis: Florida Office of Insurance Regulations for medical malpractice lawsuit data, hospital regional characteristics from the U.S. Census Bureau database, HIMSS Analytics data for HIT data, CMS HCAHPS data for measuring caregiver-patient communication quality, CMS cost reports and process-of-care data for hospital characteristics and other controls. Next, we removed 17 hospitals from our starting dataset of 188 because they did not have HCAHPS data and 3 hospitals because they reported HCAHPS data based on less than 100 respondents. Although CMS reports scores for hospitals with fewer than 100 respondents, they recommend that no conclusions be drawn for such a hospital. Therefore, we removed these 3 hospitals with HCAHPS data based on less than 100 patient responses. This yielded our final sample of data from 168 acute care hospitals in Florida.

We collected HIT adoption data from the HIMSS database, using the year in which an HIT is marked as "Live and Operational" in the HIMSS database as its year of adoption by the hospital. The use of "Live and Operational" technologies to determine HIT infrastructure at a hospital ensures that their impact on hospital processes are apparent.

4.2. Variable Descriptions

4.2.1. Dependent Variable

Adjusted Lawsuits. This variable measures the number of lawsuits brought against a hospital in a particular year. Please note, due to the lawsuit process (described in section 2.1), an actual lawsuit may have never been filed. That is, a patient may have raised a concern, met all of the criteria for a lawsuit, and notified the appropriate hospital and providers. However, due to the presuit process, this case may have been settled prior to any lawsuit being officially filed. We call all such cases lawsuits, whether or not they make it to official filing, or are resolved in the presuit process.

This lawsuit variable is derived from the Florida Office of Insurance Regulations. It should be noted that this includes all lawsuits filed—those that were settled out of or in court (including the presuit settlements), as well as any lawsuits that were filed and then dropped by the patient. This does not include lawsuits still pending settlement. By truncating our data at 2011, we ensure that a majority (~96%) of the lawsuits filed in 2011 (and a higher percentage for prior years) are settled by the time of data collection (Holman et al. 2011).

In order to account for the possibility of larger hospitals witnessing a higher number of lawsuits, we normalize the dependent variable based on the annual transfer adjusted case volume at a hospital. The annual transfer adjusted case volume is the number of patients treated by a hospital in a given year, adjusted for patient transfers to other hospitals. Specifically, we measure our dependent variable for hospital i in year t using the following equation,

$$AdjustedLawsuits_{i,t} = \frac{Number\ of\ Lawsuits_{i,t}}{Transfer\ adjusted\ cases_{i,t}}$$

4.2.2. Independent Variables

Communication Quality: This variable measures the quality of communication between caregivers and patients as perceived by the patient (Chandrasekaran et al. 2012) and reported in the HCAHPS survey. To calculate this measure, we determine a factor score based on four questions from the HCAHPS survey: (i) How often did doctors communicate well with patients? (ii) How often did nurses communicate well with patients? (iii) How often did staff explain about medicines before giving them to patients? and (iv) Were patients given information about what to do during their recovery at home? For each of these questions, CMS reports the adjusted percentages of patients who have answered the question using the response categories "never/sometimes," "usually" or "always." Consistent with previous studies (Chandrasekaran et al. 2012, Senot et al. 2015), we designate the percentage of patients who answered "always" as the measure for the items' individual scores. Results are reported on the CMS Hospital Compare website after being aggregated at the hospital level. It is also important to note that CMS adjusts these survey scores for several patient variables such as education, self-rated health, primary language, age, socio-economic status and service line. CMS also accounts for delays in the survey response (see www. hcapsonline.org for more details).

Following CMS guidelines used by other researchers (Senot et al. 2015), we included only hospitals that had a sample of more than 100 respondents for HCAHPS scores. Consistent with accepted best practices when using multiple items to measure a construct of interest, we conducted a Confirmatory Factor Analysis (CFA) to assess the convergent validity for the four communication quality scale items (Anderson and Gerbing 1988, Handley 2017, Menor and Roth 2008). We then used the resulting factor score based measure to capture communication quality. The fit indices for the CFA model were within recommended specifications (RMSEA = 0. 216; CFI = 0.971; SRMR = 0.036) indicating good model fit. All the path coefficients from the constructs to their scale items were significant ($p < 0.01$) and ranged from 0.58 to 0.97 providing strong evidence for convergent validity. We provide the detailed CFA model in the Online Appendix.

HIT: In accordance with Sharma et al. (2016), we classified HIT into three bundles (Clinical, Augmented Clinical and Administrative) based on the users of the technologies. We study the impact of augmented clinical HIT on lawsuits, and control for the clinical and administrative HIT level of hospitals. We aggregate the clinical and administrative HIT maturity of hospitals, called non-augmented clinical HIT, and add it as a control in our analysis. We measure the HIT maturity of hospitals along these two categories using a Saidin index (Queenan et al. 2011, Sharma et al. 2016, Spetz and Maiuro 2004), calculated as the weighted sum of the technologies adopted by each hospital, where the weights are inversely proportional to the number of hospitals adopting that technology. A Saidin index assigns a higher weight to rare technologies and hence gives a higher adoption score to hospitals that are leaders in the path towards increased HIT adoption, thus providing higher scores for technology leaders. These hospitals with higher scores can be considered in later cycles of adoption than their lower scored counterparts, thus more advanced in their adoption, use, and understanding of how to best use and integrate technology. Because of the technology maturity of these hospitals, they are more likely to realize higher benefits from their HIT infrastructure due to the complementary nature of these integrated HITs—as also supported by the complementarity theory (Milgrom and Roberts 1995). The Saidin index for each of the three HIT categories is calculated in the following manner:

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

where,

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

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

As a robustness test, we also replicated our analyses using count of HIT adoption (Angst et al. 2012, Boyer 1999, Ettlie 1983) instead of a Saidin index. Results remain consistent with the main analysis and are discussed in section 7 of this manuscript.

4.2.3. Control Variables. We control for hospital characteristics such as *size*, *case mix index (CMI)*, *reputation*, and *teaching intensity*, as well as population characteristics of the county served by the hospital (e.g., *wage index*, *population density*, *law firm density*). We operationalize *hospital size* using the number of beds at the hospital. *Teaching intensity* is measured as the ratio of residents to beds at a given hospital (Senot et al. 2015) and is obtained from CMS. Higher teaching intensity hospitals will likely consume more resources due to the need to train medical students and resident physicians (Grosskopf et al. 2001). In addition, the involvement of relatively inexperienced medical students and resident physicians in care delivery processes is likely to lead to more quality errors (Theokary and Ren 2011) and hence more lawsuits. Like many other studies, we control for *CMI*, a measure of the severity of illness of the patients admitted at hospitals and obtained from CMS, because hospitals treating more severe patients will face increased variability in documentation, coordination and delivery of care (Theokary and Ren 2011), making them prone to an increased number of quality errors and hence lawsuits. We also control for the hospital's *reputation* given that it sets the expectations of quality of care for the patient prior to admission and thus could influence their likelihood of filing a lawsuit against the hospital. To calculate this measure, we use the HCAHPS survey score which represents word of mouth reputation: "Would you recommend this hospital to family and friends?" A 3-point scale is used to quantify the responses to this question: definitely yes, probably yes, no. We first calculated the percentage of respondents who answered "definitely yes" to the above question and use this as a proxy for hospital reputation. Given the high correlation between the communication quality and reputation measure (due to their origins from the HCAHPS survey), we created an orthogonal construct for the hospital reputation measure through sequential regression (Hastie et al. 2009, Nagar and Rajan 2005, Ridker and Henning 1967, Sine et al. 2003) and used it as a control in our regression models.

The number of lawsuits may also be impacted by the actual quality of care delivered by the hospitals. Accordingly, we control for a number of factors indicative of the quality of care at a hospital. Specifically, we control for the average patient *length of stay* and *conformance quality* at the hospital. Research has demonstrated that length of stay performance is related to efficiency, quality of care and responsiveness (Ashby et al. 2000, Glick et al. 2003, Thomas et al. 1997), all of which are factors that can impact lawsuits. We also control for a hospital's score on CMS quality of care measures. A higher score on the CMS quality of care measures is an indication of better adherence to evidence-based care protocols, which should result in lower likelihood of lawsuits. A logit transformation (Collett 2003) of the weighted average (P_i) of the percentage compliance along four dimensions, namely Heart Attack (AMI), Heart Failure (HF), Pneumonia (PN), and Surgical Care Improvement Project (SCIP) is used to measure conformance quality (Chandrasekaran et al. 2012, Sharma et al. 2016). The conformance quality $C_{i,t}$ for a hospital i and time period t with a compliance percentage $P_{i,t}$ is given by the following:

$$C_{i,t} = Ln\left[\frac{Pi, t}{1 - Pi, t}\right]$$

We also control for the *wage index* in the county served by the hospitals. A higher wage index is an indication of a prosperous area, which should reduce the likelihood of low payout lawsuits. A control for *population density* of the county served by the hospital is added to account for the degree of urbanization of the region served by the hospital. Finally, using a log transformation of the number of law firms located in the county served by the hospital, we control for *law firm concentration*. We control for this because a higher concentration of law firms indicates increased competition as well as greater options available for patients to file lawsuits against hospitals. In addition to the above measures, we also control for *non-Augmented Clinical HIT*, which is measured using a sum of the Saidin index of Clinical and Administrative HIT systems. Dummy variables for each year were added in the regression model to control for *year fixed effects*. Table 1 shows summary statistics and correlations for our variables.

5. Model Specification

The dependent variable for this study is fractional with values restricted below one and bounded at zero, with a large number of values at 0. This type of bounded fractional continuous dependent variable has unique distributional characteristics which reduce the applicability of linear regression models for analysis. Specifically, no restrictions on predicted values outside the bounds for the dependent variable and inability to account for non-constant responses near the bounds can result in biased estimates when using linear regression models (Papke and Wooldridge 1996, 2008, Rigobon and Stoker 2007). Although truncated and censored regression models are better equipped to handle bounded fractional continuous dependent variables, these methods have limitations of their own. For instance, Tobit regression, used for censored data, is sensitive to heteroskedasticity issues and has a normality requirement for the error terms (Arabmazar and Schmidt 1981, Wooldridge 2002). Further, some researchers (e.g., Papke and Wooldridge 1996, 2008) argue that a Tobit regression should not be used when values beyond the censoring point are infeasible, which is the case in this situation. A fractional response model (FRM), developed by Papke and Wooldridge (1996), overcomes these limitations and has been increasingly used in analyzing bounded fractional continuous dependent variables (Chen et al. 2015, Core et al. 2008, Papke and Wooldridge 1996, 2008). For example, Core et al. (2008)

Table 1 Summary Statistics and Correlations

		Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12
1	Case mix index	1.44	0.22	1											
2	Beds	284.02	221.97	0.64*	1										
3	Resident to bed ratio	0.02	0.07	0.36*	0.52*	1									
4	HIT	4.82	1.93	0.30*	0.18*	0.06	1								
5	Non-augmented clinical HIT	12.49	4.13	0.39*	0.23*	0.02	0.60*	1							
6	Population density	924.07	1035.08	0.14*	0.19*	0.10*	0.06	0.15	1						
7	Conformance quality	3.10	1.18	0.29*	0.13*	−0.05	0.33*	0.38*	0.37*	1					
8	Communication quality	0.00	4.256	−0.01	−0.02	0.04	−0.01	0.12*	−0.11*	0.09*	1				
9	Wage index	0.93	0.05	0.10*	0.15*	0.06	−0.01	−0.12*	0.21*	0.14*	−0.15*	1			
10	Normalized number of lawsuits	0.0016	0.0046	−0.16*	−0.15*	−0.06	−0.11*	−0.13*	−0.01	−0.09	0.02	0.01	1		
11	Length of stay	4.56	0.85	0.34*	0.39*	0.32*	−0.05	0.03	0.16*	−001	0.02	0.20*	−0.01	1	
12	Law firm concentration	5.83	1.73	0.33*	0.40*	0.19*	0.07*	0.22*	0.50*	0.22*	−0.11*	0.62*	−0.04	0.31*	1
13	Hospital reputation (orthogonal construct)	0	0.288	0.36*	0.23*	0.07*	0.15*	0.24*	0.11*	0.00	0.00	0.10*	−0.08*	0.02	0.17*

Note: "HIT" is our hypothesized technology variable of interest, Non-augmented clinical HIT is a control variable. $*p < 0.05$.

(Row 13 also has a final entry "1" in a column beyond column 12.)

used an FRM to accommodate their dependent variable (fraction of press articles with negative coverage about CEO compensation), which was left censored with a median value of zero. Similarly, Papke and Wooldridge (1996) used an FRM to model participation rates of employees in firms' 401(k) retirement plans, which involved right censoring of the dependent variable with a large number of values at 1.

An FRM is an extension of the generalized linear model (GLM), which uses a quasi-maximum likelihood estimator (QMLE). A QMLE generates consistent estimates of the regression coefficients irrespective of the distribution of the dependent variable. Other advantages of an FRM are that it accounts for the nonlinearity in the data introduced due to censoring, does not require a correction or transformation to account for the observations at the lower or upper bounds of the data and it is robust and efficient under GLM model assumptions (Gallani et al. 2015). Considering these relative advantages of FRMs, we use it to test our hypotheses.

Although an FRM is appropriate for modeling bounded fractional continuous-dependent variables and reduces biases due to incorrect modelling, there are other potential sources of bias in our analysis. Specifically, there is potential for omitted variables, which could introduce endogeneity concerns in our analysis. Potential omitted variables could be patient level characteristics, including personal inclinations and biases, which could potentially influence their likelihood to file lawsuits against hospitals following a quality failure. Thus, we take a number of steps to account and adjust for sources of such unobserved heterogeneity. First, we control for a number of hospital and market level factors like quality proxies (length of stay and conformance quality) in our main analysis. Second, we use an instrumental variable FRM to account for endogeneity concerns.

For the instrumental variable FRM, we used lagged values of the endogenous variables, that is, one-year-lagged values of HIT and communication quality, and average HIT and communication quality of hospitals (excluding the focal hospital) located within a health referral region (HRR), as instruments. Lagged values of endogenous variables have been used as instruments for endogenous variables in a number of recent studies (Bloom and Van Reenen 2007, Kesavan et al. 2014, Siebert and Zubanov 2010, Tan and Netessine 2014). For lagged values of endogenous variables to be valid instruments, they must correlate with the contemporaneous values of these variables and be independent of the error terms. Since HIT variables are expensive to procure and generally have an associated implementation period, it is unlikely for hospitals to drastically change their HIT infrastructure over a short time period. These high procurement costs and implementation time will ensure that lagged values of our HIT variables are correlated with their contemporaneous values satisfying the first condition. Similarly, communication quality involves extensive investments in caregiver training, amenities, and a cultural transformation. These factors ensure that communication quality scores do not change drastically over a short time period, thus making their lagged values correlated with their contemporaneous values. In order to test for the independence of the lagged communication quality and HIT instruments with the error terms we performed the Arellano–Bond (1991) test for autocorrelation. To determine the *n*th order serial correlation, this test looks for correlation of order $n + 1$ in the differences of the residuals. The test turns out to be insignificant ($p > 0.1$), indicating lags 1 and higher can be used as instruments for the endogenous variables. Based on these tests, we use 1-year-lagged values of HIT and communication quality as instruments in our model.

The second set of instruments represent the bandwagon effect (i.e., the tendency to mimic competition), which can influence hospitals' HIT adoption decisions as well as investments made in improving communication quality (Abrahamson and Rosenkopf 1993). Hospital referral regions (HRRs) represent regional health care markets which define the likely patient pool and competition set for a hospital. We use the average HIT adoption and communication quality scores for competing hospitals in the HRR as an instrument for the endogenous variables.

As another instrument validity test, we also note that the excluded instruments in the first stage regression models all have *F*-statistics that are greater than the threshold of 10 (Staiger and Stock 1994), indicating that they are not weak instruments. In addition, the Sargen test, with the null hypotheses that the instruments used are jointly valid, also turns out to be insignificant ($p > 0.10$) which supports the joint validity of our instruments. All of these tests provide confidence in the choice of the instruments. Finally, given the non-linear nature of our model we use a control function approach, which substitutes the predicted error terms from the first stage into the main model, to address endogeneity (Lin and Wooldridge 2017, Wooldridge 2015). We use a probit link function with the FRM due to its underlying normal distributional assumption which makes it better-suited with the control function approach (Papke and Wooldridge 2008). The regression equation modelling share of patients who file lawsuits against the hospital i in time period t is presented below:

$$Y_{i,t} = X_{i,t}\beta + Z_{i,t}\gamma + \varepsilon_{i,t},$$

where, $Y_{i,t}$ is the share of patients who file a lawsuits against the hospital, $X_{i,t}$ is the vector of exogenous regressors and $Z_{i,t}$ is the vector of endogenous regressors. For an FRM, the expected value of the share of patients who file a lawsuit against the hospital is given by

$$E(Y_{i,t}|X_{i,t}, Z_{i,t}, \hat{\xi}_{i,t}) = \phi\left(X_{it}\beta + Z_{i,t}\gamma + \hat{\xi}_{i,t}\right)$$

where Φ is the cdf of standard normal distribution and vector has the predicted residuals from the first stage regressions of endogenous regressors on all other controls. All of the continuous variables in the regression models are mean centered. We use robust standard errors. Because we are using a two-step estimation process, we used bootstrapped standard errors (500 replications) to correct for the first stage estimation. We present the results from these regressions (bootstrapped FRM estimates using control function approach to correct for endogeneity) in Table 2.

6. Results

6.1. Hypotheses Testing

Hypothesis 1 posits that hospitals with higher HIT maturity are less likely to be sued compared to hospitals with lower HIT maturity. As seen from Table 2, the coefficient for HIT is negative and significant ($\beta = -.045$; $p < 0.05$), providing support for H1. Although parameter estimates and their standard errors can help establish a causal link between covariates and the dependent variable, determining the effect sizes of covariates requires additional calculations given the non-linear nature of the FRM model. Specifically, the impact of change in HIT on adjusted lawsuits is given by the following:

$$\frac{dE(Y_{i,t}|X_{i,t}, Z_{i,t}, \hat{\xi}_{i,t})}{d(HIT_{i,t})} = \phi\left(X_{it}^{\beta} + Z_{i,t}\gamma + \hat{\xi}_{i,t}\right)\gamma_{HIT}.$$

Based on the above equation, we can ascertain that (unlike linear models) the coefficient estimate for HIT is only an indication of the directionality of its impact but not the magnitude. The magnitude of the impact depends on value of the normal pdf at the predicted value of the latent index and the coefficient of HIT for any given observation. Finally, there is heterogeneity in the marginal effects of HIT (unlike linear models which have constant marginal effects). Due to this heterogeneity we report the average marginal effects of HIT at different values over its range: 5th, 25th, 50th, 75th and 95th percentiles, in Table 3. Also in Table 3, we translate these marginal effects to number of lawsuits and dollar impact on the hospital.

Table 2 Instrumental Variable Fractional Response Model with Bootstrapped Standard Errors to Determine Effect of HIT, Communication Quality, and Their Interaction on Adjusted Lawsuits

	Hypothesis 1			Hypothesis 2		
	Coeff.	SE	95% CI	Coeff.	SE	95% CI
Communication quality	0.001	0.010	(−0.018, 0.021)	−0.003	0.009	(−0.020, 0.014)
HIT	−0.045**	0.021	(−0.086, −0.003)	−0.042**	0.021	(−0.083, −0.001)
Communication quality × HIT				−0.011**	0.004	(−0.020, −0.001)
Constant	−3.042***	0.055	(−3.150, −2.934)	−3.052***	0.051	(−3.153, −2.951)
Case mix index	−0.365*	0.189	(−0.736, 0.006)	−0.326*	0.172	(−0.664, 0.010)
Wage index	.407	0.739	(−1.042, 1.856)	0.345	0.713	(−1.053, 1.744)
Number of beds	−0.0003*	0.0002	(−0.0007, 0.0000)	−0.0004**	0.0002	(−0.0007, −0.0000)
Length of stay	−0.109**	0.052	(−0.212, −0.007)	−0.110***	0.045	(−0.200, −0.020)
Resident to bed ratio	0.443	0.434	(−0.407, 1.293)	0.411	0.481	(−0.533, 1.355)
Conformance quality	−0.033	0.025	(−0.084, 0.016)	−0.032	0.025	(−0.083, 0.017)
Population density	0.000	0.000	(−0.000, 0.000)	0.000	0.000	(−0.000, 0.000)
Non-augmented clinical HIT	0.012	0.008	(−0.004, 0.030)	.019**	0.008	(0.003, 0.036)
Law firm concentration	−0.006	0.027	(−0.060, 0.047)	−0.004	0.025	(−0.054, 0.045)
Hospital reputation	−0.052	0.121	(−0.290, 0.185)	−0.004	0.122	(−0.244, 0.235)
Pseudo R^2		0.04			0.05	
p-value		0.00			0.00	
Observations		548			548	

Notes: “HIT” is our hypothesized technology variable of interest, Non-augmented clinical HIT is a control variable. Lagged values of communication quality and HIT, and average Augmented Clinical HIT and communication quality of hospitals located within a health referral region (HRR) are used as instruments for communication quality and HIT. 500 bootstrap replications were performed. All regressions were run with year fixed effects. Predicted residuals from the first stage are added as controls. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table 3 Marginal Effects at Different Percentiles of HIT Using a Fractional Response Model

	Marginal effects				
Percentiles for HIT	Coeff.	SE	95% CI	Number of lawsuits	Dollar impact on hospitals
5th percentile	−0.00034	0.00028	(−0.00088, 0.00021)	−1.6314	$570,981
25th percentile	−0.00025	0.00013	(−0.00051, 0.00001)	−1.1958	$418,540
50th percentile	−0.00022	0.00011	(−0.00043, −0.00001)	−1.0599	$370,986
75th percentile	−0.00018	0.00008	(−0.00034, −0.00001)	−0.8696	$304,377
95th percentile	−0.00013	0.00005	(−0.00024, −0.00002)	−0.6456	$225,964

Notes: Marginal effects are calculated by setting all other independent variables to their means. Number of lawsuits are calculated by multiplying the marginal effects with the mean transfer adjusted volume of 4818 patients. The number of lawsuits represent the reduction in lawsuits experienced by the hospital when adding HIT equivalent of 1 Saidin index. The dollar impact of lawsuit reduction on hospitals is calculated by using an average lawsuit cost of $350,000, reached by averaging the payouts of all lawsuits in our data set ($282,000) and adding an additional $0.19 (per $1 in settlement) for costs associated with defendant lawyer fees, etc. given this estimate in additional fees per Mello et al. (2010).

From Table 3, we see that an increase in HIT reduces the number of lawsuits filed against a hospital, with this effect being larger at early cycles of HIT adoption. Another way of saying this is that as the HIT infrastructure of the hospital matures, the incremental benefits on lawsuit reduction decreases. For example, for hospitals at the 5th percentile of HIT adoption, a unit Saidin index increase in HIT will result in a reduction of 1.63 lawsuits. This reduction of 1.63 lawsuits can translate to $570,981 in cost savings. The cost savings are calculated based on an average lawsuit cost of $350,000, reached by averaging the payouts of all lawsuits in our data set ($282,000) and adding an additional $0.19 (per $1 in settlement) for costs associated with defendant lawyer fees, etc. given this estimate in additional fees per Mello et al. (2010). On the other hand, for hospitals at the 95th percentile of HIT adoption, a unit Saidin index increase in HIT will result in a reduction of 0.65 lawsuits translating to a cost savings of $225,964. Assuming the average HIT score for our sample hospitals, a unit Saidin index increase in HIT results in a 1.12 reduction in lawsuits translating into cost savings of $391,896 for hospitals. Note that because the Saidin index is a dynamic number which changes as more hospitals adopt each technology, a unit change in the Saidin index will change over time and will depend on the HITs adopted. However, for intuitional insights, one can approximate a unit Saidin index increase to an adoption of three additional HIT technologies, for an average hospital.

Hypothesis 2 posits that the interaction of HIT and communication quality is associated with the number of lawsuits filed against the hospital, where communication quality amplifies the positive effect of HIT in reducing lawsuits. As seen from Table 2, the coefficient of the interaction term between communication quality and HIT is negative and significant ($\beta = -.011$; $p < 0.05$), indicating that as both HIT and communication quality increase, together, they reduce lawsuits. Determining the effect sizes of covariates requires taking a derivative of the response function. Specifically, the impact of a change in HIT on adjusted lawsuits for any observation is given by,

$$\frac{dE(Y_{i,t}|X_{i,t}, Z_{i,t}, \hat{\xi}_{i,t})}{d(HIT_{i,t})} = \phi\left(X_{it}\beta + Z_{i,t}\gamma + \hat{\xi}_{i,t}\right)(\gamma_{HIT} + \gamma_{HIT*Comm} Communication\ Quality).$$

Based on the above equation, we can ascertain that the marginal effect of HIT will depend on the value of the normal pdf for a given observation, coefficient of HIT, coefficient of the interaction term between HIT and communication quality, as well as the level of communication quality. Finally, due to the nonlinear nature of the estimation model there will be heterogeneity in the marginal effects of HIT based on the level of HIT and communication quality at the hospital. Due to this heterogeneity we report the averaged marginal effects of HIT at different values over its range: 5th, 25th, 50th, 75th and 95th percentiles and for three levels of communication quality—low (5th percentile), medium (50th percentile) and high (95th percentile). These average marginal effects of HIT in terms of adjusted lawsuits, number of lawsuits and dollar impact on the hospital are reported in Table 4.

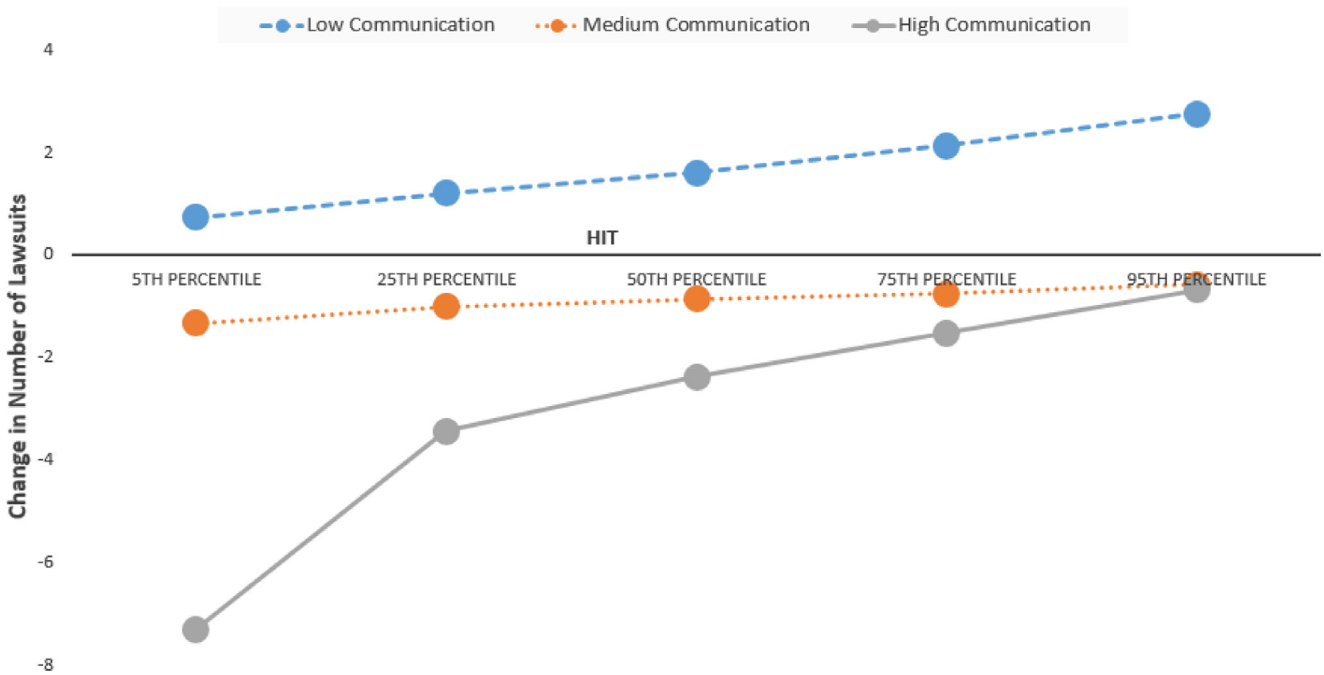
To illustrate the results shown in Table 4, we graph the marginal change in number of lawsuits filed for low, medium and high communication hospitals at varying levels of HIT adoption in Figure 2. As evident from Figure 2, as hospitals with low communication quality adopt more HIT, they have a marginal increase in lawsuits (points are above the zero line, and hence lawsuits are increasing). Conversely, as hospitals with high communication quality adopt more HIT, they experience a marginal decrease in lawsuits (points are below the zero line, and hence they are experiencing a reduction in lawsuits). The magnitude of this effect changes as a hospital's HIT infrastructure matures. As an example, consider a hospital with high communication quality (95th percentile). If this hospital is at the 5th percentile of HIT adoption, a unit Saidin index increase in HIT will result in a reduction of 7.29 lawsuits translating into a cost savings of $2,551,372. If this same hospital is at the 95th percentile of HIT adoption, a unit Saidin index increase in HIT will result in a reduction of 0.68 lawsuits translating in a cost savings of $239,286. On the other hand, let us consider a hospital with low communication quality (5th percentile) and with low HIT adoption (5th percentile). If this hospital increases HIT by one unit of the Saidin index, this hospital will witness a 0.72 lawsuit increase

Table 4 Marginal Effects at Different Percentiles of HIT for Low, Medium and High Communication Quality Using a Fractional Response Model

		Marginal effects				
	Percentiles for HIT	Coeff.	SE	95% CI	Number of lawsuits	Dollar impact
Low communication (5th percentile)	5th	0.00015	0.00008	(0.00000, 0.00031)	0.722	$252,945
	25th	0.00025	0.00012	(0.00001, 0.00049)	1.204	$421,575
	50th	0.00033	0.00022	(−0.00010, 0.00076)	1.589	$556,479
	75th	0.00044	0.00038	(−0.00031, 0.00118)	2.119	$741,972
	95th	0.00057	0.00058	(−0.00057, 0.00171)	2.746	$961,191
Medium communication (50th percentile)	5th	−0.00028	0.0002	(−0.0007, 0.0001)	−1.337	$468,117
	25th	−0.00021	0.0001	(−0.0005, 0.0000)	−1.011	$353,954
	50th	−0.00018	0.0001	(−0.0004, −0.0000)	−0.867	$303,534
	75th	−0.00016	0.0001	(−0.0003, −0.0000)	−0.759	$265,930
	95th	−0.00012	0.0000	(−0.0003, −0.0000)	−0.582	$203,874
High communication (95th percentile)	5th	−0.00151	0.00105	(−0.00357, 0.00055)	−7.289	$2,551,372
	25th	−0.00071	0.00034	(−0.00139, −0.00003)	−3.441	$1,204,355
	50th	−0.00049	0.00019	(−0.00087, −0.00011)	−2.375	$831,515
	75th	−0.00031	0.00009	(−0.00050, −0.00012)	−1.522	$533,039
	95th	−0.00014	0.00003	(−0.00020, −0.00007)	−0.683	$239,286

Notes: Marginal effects are calculated by setting all other independent variables to their means. Number of lawsuits are calculated by multiplying the marginal effects with the mean transfer adjusted volume of 4818 patients. The number of lawsuits represent the reduction in lawsuits experienced by the hospital when adding HIT equivalent to 1 Saidin index. The dollar impact of lawsuit reduction on hospitals is calculated by using an average lawsuit cost of $350,000, reached by averaging the payouts of all lawsuits in our data set ($282,000) and adding an additional $0.19 (per $1 in settlement) for costs associated with defendant lawyer fees, etc. given this estimate in additional fees per Mello et al. (2010).

Figure 2 Marginal Effects Plot for the Interaction between Communication Quality and HIT in Predicting Lawsuits [Color figure can be viewed at wileyonlinelibrary.com]



translating into $252,945 of additional expenses. If this same hospital is at the 95th percentile of HIT adoption, a unit Saidin index increase in HIT will result in an even larger increase of 2.75 lawsuits translating into $961,191 of additional expenses. Please note that the marginal effects for hospitals with low communication quality and/or high HIT adoption (e.g., 95th HIT and 5th communication quality percentile) are not significant at $p < 0.05$. This lack of significance at the extremes of HIT adoption and/or communication quality could be due to the smaller sample size in these groups and the resulting large confidence interval.

Assuming the average HIT score for our sample hospitals, a hospital with low communication quality which increases its HIT by one unit Saidin index can expect an increase of 1.55 lawsuits (cost increase of $541,976). On the other hand, hospitals with medium communication quality that increases HIT by one unit Saidin index can expect 0.85 fewer lawsuits (cost savings of $298,475), while hospitals with high communication quality experience 2.38 fewer lawsuits (cost savings of $833,032).

6.2. Additional Analysis

6.2.1. Different Caregiver Profiles. As an alternate to the aggregate measure of communication quality, we investigate whether support for our hypotheses differs based on who is communicating; specifically, we analyze nurse communication quality separately from physician communication quality. To study these relationships, we examine the physician and nurse communication components of the HCAHPS survey. The physician communication quality score is calculated as the percentage of patients who answered "always" as the measure for the HCAHPS survey items: "How often did doctors communicate well with patients?" Similarly, the nurse communication quality score is calculated as the percentage of patients who answered "always" as the measure for the HCAHPS survey items: "How often did nurses communicate well with patients?" We then use an instrumental variable fractional response model with bootstrapped standard errors to study the relationship between communication quality (nurse or physician) and HIT on number of lawsuits filed against the hospital. We used lagged values of the endogenous variables, that is, 1-year-lagged values of HIT adoption and communication quality (nurse or physician communication), and average HIT and communication quality (nurse or physician communication) of competing hospitals located within a health referral region (HRR), as instruments. We present these results in Table 5.

The interaction effects between HIT and communication are significant for both physician and nurse communication. Regarding physician communication quality, we observe a similar pattern of results as the main analysis. That is, while increasing HIT with low physician communication quality increases lawsuits there are positive synergies between these two factors as physician communication quality improves. Specifically, on an

Table 5 Instrumental Variable Fractional Response Model with Bootstrapped Standard Errors to Determine Effect of HIT, Physician and Nurse Communication, and Their Interaction on Adjusted Lawsuits

	Physician communication			Nurse communication		
	Coeff.	SE	95% CI	Coeff.	SE	95% CI
Physician communication	0.001	0.005	(−0.009, 0.010)			
Nurse communication				−0.001	0.006	(−0.012, 0.011)
HIT	−0.037*	0.022	(−0.080, 0.006)	−0.039*	0.023	(−0.084, 0.006)
Physician communication × HIT	−0.006*	0.003	(−0.011, 0.000)			
Nurse communication × HIT				−0.008**	0.003	(−0.014, −0.001)
Constant	−3.010***	0.064	(−3.137, −2.883)	−3.003***	0.063	(−3.128, −2.879)
Case mix index	−0.291*	0.175	(−0.635, 0.051)	−0.298*	0.173	(−0.637, 0.041)
Wage index	0.397	0.742	(−1.057, 1.852)	0.276	0.736	(−1.166, 1.719)
Number of beds	−0.0003*	0.0001	(−0.0007, 0.0000)	−0.0004**	0.0002	(−0.0007, −0.0000)
Length of stay	−0.136**	0.056	(−0.247, −0.025)	−0.124**	0.051	(−0.225, −0.024)
Resident to bed ratio	0.642	0.539	(−0.415, 1.700)	0.593	0.539	(−0.463, 1.649)
Conformance quality	−0.026	0.028	(−0.083, 0.030)	−0.043	0.029	(−0.101, 0.014)
Population density	0.000	0.000	(−0.000, 0.000)	0.000	0.000	(−0.000, 0.000)
Non-augmented clinical HIT	0.016**	0.008	(0.000, 0.033)	0.019**	0.008	(0.002, 0.036)
Law firm concentration	−0.011	0.030	(−0.070, 0.047)	−0.001	0.027	(−0.056, 0.052)
Hospital reputation	−0.063	0.154	(−0.365, 0.239)	−0.088	0.133	(−0.351, 0.173)
Pseudo R^2		0.04			0.04	
p-value		0.00			0.00	
Observations		548			548	

Notes: "HIT" is our hypothesized technology variable of interest, Non-augmented clinical HIT is a control variable. Lagged values of communication quality (physician and nurse communication respectively) and HIT, and average Augmented Clinical HIT and communication quality (physician and nurse communication respectively) of hospitals located within a health referral region (HRR) are used as instruments for communication quality (physician and nurse communication respectively) and HIT. 500 bootstrap replications were performed. All regressions were run with year fixed effects. Predicted residuals from the first stage are added as controls. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

average with a unit Saidin index increase in HIT, hospitals with low physician communication quality (5th percentile) witness a 0.95 increase in lawsuits (cost increase of $331,357). On the other hand, hospitals with medium physician communication quality (50th percentile) witness a 0.81 reduction in lawsuits (cost savings of $285,153), while a 2.21 lawsuit reduction (cost savings of $772,662) is witnessed by hospitals with high physician communication quality (95th percentile). Similar to the main analysis, there is a heterogeneity in this relationship based on the level of HIT, with positive synergies between HIT and physician communication (at medium to high levels) in reducing lawsuits being stronger in early cycles of HIT adoption. On the other hand, the observed increase in lawsuits at low physician communication levels become stronger as the HIT adoption at a hospital increases.

Nurse communication behaves in a similar manner as physician communication in influencing the relationship between HIT and lawsuits. While increasing HIT at low nurse communication quality increases lawsuits, there are positive synergies between these two factors as nurse communication quality improves. Specifically, for hospitals with low nurse communication quality, a unit Saidin index increase in HIT will, on average, yield 0.88 more lawsuits (cost increase of $308,087). On the other hand, hospitals with medium nurse communication quality witness a 1.05 reduction in lawsuits (cost savings of $365,927), while a 2.46 lawsuit reduction (cost savings of $861,699) is witnessed by hospitals with high nurse communication quality. The heterogeneity in effect sizes based on the level of HIT adoption is also consistent with the observations for physician communication.

6.2.2. Different Severities of Lawsuits. As an additional analysis, we investigate whether support for our hypotheses differ based on the severity of the injury driving the lawsuit. The Florida Office of Insurance Regulations for medical malpractice lawsuit database classifies lawsuits into six categories based on severity of injury: emotional trauma, minor temporary organ damage, minor permanent organ damage, major temporary organ damage, major permanent organ damage, and death. The first three categories are classified as low severity lawsuits; the remaining categories, high severity lawsuits. We present the analysis results in Table 6; the results for the low severity and high severity lawsuits are consistent with the main analysis.

Similar to the main analysis, the interaction between HIT and communication quality is significant and negative for both low severity and high

Table 6 Instrumental Variable Fractional Response Model with Bootstrapped Standard Errors to Determine Effect of HIT, Communication, and Their Interaction on Adjusted High and Low Severity Lawsuits

	Adjusted high severity lawsuits			Adjusted low severity lawsuits		
	Coeff.	SE	95% CI	Coeff.	SE	95% CI
Communication quality	0.002	0.008	(−0.015, 0.018)	−0.006	0.011	(−0.028, 0.015)
HIT	−0.063**	0.027	(−0.118, −0.009)	−0.036	0.029	(−0.094, 0.020)
Communication quality × HIT	−0.010**	0.005	(−0.020, −0.000)	−0.010**	0.005	(−0.020, −0.000)
Constant	−3.296***	0.052	(−3.399, −3.192)	−3.296***	0.065	(−3.424, −3.168)
Case mix index	−0.236	0.191	(−0.612, 0.138)	−0.421**	0.166	(−0.748, −0.095)
Wage index	1.087	0.791	(−0.464, 2.638)	−0.259	0.707	(−1.647, 1.127)
Number of beds	−0.0003	0.0002	(−0.0006, 0.0001)	−0.0004**	0.0002	(−0.0007, −0.0001)
Length of stay	−0.145***	0.051	(−0.245, −0.044)	−0.075	0.048	(−0.171, 0.020)
Resident to bed ratio	0.310	0.556	(−0.780, 1.402)	0.592	0.392	(−0.177, 1.361)
Conformance quality	−0.040	0.028	(−0.097, 0.015)	−0.040	0.025	(−0.091, 0.010)
Population density	0.000	0.000	(−0.000, 0.000)	−0.000	0.000	(−0.000, 0.000)
Non-augmented clinical HIT	0.013***	0.004	(0.004, 0.022)	0.015***	0.004	(0.005, 0.024)
Law firm concentration	−0.012	0.029	(−0.069, 0.045)	0.004	0.025	(−0.047, 0.054)
Hospital reputation	−0.002	0.144	(−0.285, 0.281)	−0.036	0.108	(−0.250, 0.176)
Pseudo R^2		0.04			0.04	
p-value		0.00			0.00	
Observations		548			548	

Notes: "HIT" is our hypothesized technology variable of interest, Non-augmented clinical HIT is a control variable. Lagged values of communication quality and HIT, and average Augmented Clinical HIT and communication quality of hospitals located within a health referral region (HRR) are used as instruments for communication quality and HIT. 500 bootstrap replications were performed. All regressions were run with year fixed effects. Predicted residuals from the first stage are added as controls. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

severity injury lawsuits. For high severity lawsuits, on an average with a unit Saidin index increase in HIT, hospitals with low communication quality (5th percentile) witness a 0.43 increase in lawsuits. On the other hand, hospitals with medium communication quality (50th percentile) witness a 0.73 reduction in lawsuits, while a 1.66 lawsuit reduction is witnessed by hospitals with high communication quality. For low severity lawsuits, on an average with a unit Saidin index increase in HIT, hospitals with low communication quality witness a 0.87 increase in lawsuits. On the other hand, hospitals with medium communication quality witness a 0.39 reduction in lawsuits, while a 1.01 lawsuit reduction is witnessed by hospitals with high communication quality. Overall, the relationships between HIT and lawsuits for high communication quality remains consistent with the main analysis irrespective of the type of injury.

7. Robustness Checks

We conduct several additional analyses to demonstrate the robustness of our findings. First, we analyze our model using alternate normalizations for the number of lawsuits. Both annual patient days and number of beds are alternate measures of a hospital's scale of operations. The average patient days for hospital i and year t is calculated as,

$$Annual\ Patient\ Days_{i,t} = Average\ Daily\ Census_{i,t} \times 365.$$

The alternate measures of adjusted lawsuits using the two measures of a hospital's scale of operations for hospital i and year t are calculated as follows:

$$Adjusted\ Law\ suits\ perbed_{i,t} = \frac{Number\ of\ Law\ suits_{i,t}}{Number\ of\ beds_{i,t},}$$

and

$$Adjusted\ Law\ suits\ per\ patient\ day_{i,t} = \frac{Number\ of\ Law\ suits_{i,t}}{Annual\ Patient\ Days_{i,t}}$$

Using these alternate normalizations of lawsuits, we analyze an instrumental variable FRM with bootstrapped standard errors. The results from these models are presented in Table 7 and remain consistent with the main analysis.

Second, as an alternate to a Saidin index we use count of technologies to capture augmented and non-augmented Clinical HIT. A number of studies have used count as a measure of HIT levels (Angst et al. 2012, Boyer 1999, Ettlie 1983). We present the results of the instrumental variable fractional response model with bootstrapped errors using count for HIT in Table 8; the results remain consistent with the main analysis in both directionality and magnitude.

Third, we used an alternate measure of communication quality to test hypothesis 1 and 2. To calculate this measure, we averaged four questions from the HCAHPS survey (Q_i) and then applied a logit

Table 7 Instrumental Variable Fractional Response Model with Bootstrapped Standard Errors to Determine Effect of HIT, Communication, and Their Interaction on Alternate Measures of Lawsuits

	Lawsuits per bed			Lawsuits per patient days		
	Coeff.	SE	95% CI	Coeff.	SE	95% CI
Communication quality	−0.018	0.012	(−0.043, 0.006)	−0.006	0.007	(−0.021, 0.009)
HIT	−0.049*	0.028	(−0.104, 0.006)	−0.044**	0.019	(−0.082, −0.007)
Communication quality × HIT	−0.013**	0.006	(−0.024, −0.000)	−0.009***	0.004	(−0.017, −0.000)
Constant	−2.098***	0.069	(−2.234, −1.963)	−3.748***	0.045	(−3.836, −3.660)
Case mix index	0.010	0.215	(−0.412, 0.434)	−0.177	0.153	(−0.478, 0.122)
Wage index	−1.051	0.906	(−2.827, 0.724)	−0.282	0.503	(−1.268, 0.704)
Number of beds	−0.001***	0.000	(−0.001, −0.000)	−0.0005***	0.0002	(−0.0009, −0.0002)
Length of stay	−0.113**	0.053	(−0.218, −0.008)	−0.100**	0.039	(−0.177, −0.022)
Resident to bed ratio	0.987*	0.562	(−0.114, 2.089)	0.289	0.374	(−0.444, 1.022)
Conformance quality	−0.030	0.036	(−0.101, 0.040)	−0.015	0.023	(−0.061, 0.030)
Population density	−0.000	0.000	(−0.000, 0.000)	0.000	0.000	(−0.000, 0.000)
Non-augmented clinical HIT	0.023*	0.012	(−0.001, 0.048)	0.016**	0.008	(0.000, 0.033)
Law firm concentration	−0.011	0.033	(−0.077, 0.054)	−0.028	0.021	(−0.069, 0.013)
Hospital reputation	0.030	0.142	(−0.249, 0.310)	0.030	0.103	(−0.171, 0.232)
Pseudo R^2		0.07			0.05	
p-value		0.00			0.00	
Observations		548			548	

Notes: "HIT" is our hypothesized technology variable of interest, Non-augmented clinical HIT is a control variable. Lagged values of communication quality and HIT, and average Augmented Clinical HIT and communication quality of hospitals located within a health referral region (HRR) are used as instruments for communication quality and HIT. Here 500 bootstrap replications were performed. All regressions were run with year fixed effects. Predicted residuals from the first stage are added as controls. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table 8 Instrumental Variable Fractional Response Model with Bootstrapped Standard Errors to Determine Effect of HIT, Communication, and Their Interaction on Adjusted Lawsuits Using Alternate Measures of HIT (Count) and Communication Quality (logit transformed score)

	Alternate measure of HIT (count)			Alternate measure of communication quality		
	Coeff.	SE	95% CI	Coeff.	SE	95% CI
Communication quality	−0.001	0.009	(−0.019, 0.016)	−0.010	0.147	(−0.298, 0.277)
HIT	−0.028**	0.013	(−0.055, −0.001)	−0.040*	0.023	(−0.086, 0.004)
Communication quality × HIT	−0.006**	0.002	(−0.011, −0.001)	−0.165**	0.080	(−0.322, −0.007)
Constant	−3.078***	0.051	(−3.180, −2.976)	−2.998***	0.063	(−3.123, −2.873)
Case mix index	−0.354**	0.169	(−0.686, −0.023)	−0.312*	0.178	(−0.662, 0.036)
Wage index	0.453	0.706	(−0.932, 1.838)	0.363	0.755	(−1.117, 1.843)
Number of beds	−0.0003**	0.0002	(−0.0007, −0.0000)	−0.0003*	0.0002	(−0.0007, 0.0000)
Length of stay	−0.115**	0.049	(−0.211, −0.018)	−0.130**	0.053	(−0.234, −0.025)
Resident to bed ratio	0.415	0.487	(−0.540, 1.370)	0.586	0.545	(−0.482, 1.655)
Conformance quality	−0.040	0.026	(−0.091, 0.010)	−0.037	0.029	(−0.094, 0.019)
Population density	0.000	0.000	(−0.000, 0.000)	0.000	0.000	(−0.000, 0.000)
Non-augmented clinical HIT	0.017***	0.004	(0.007, 0.026)	0.019**	0.008	(0.002, 0.035)
Law firm concentration	−0.006	0.025	(−0.055, 0.043)	−0.006	0.028	(−0.063, 0.049)
Hospital reputation	−0.017	0.122	(−0.256, 0.221)	−0.082	0.147	(−0.371, 0.2066)
Pseudo R^2		0.04			0.04	
p-value		0.00			0.00	
Observations		548			548	

Notes: "HIT" is our hypothesized technology variable of interest, Non-augmented clinical HIT is a control variable. Lagged values of communication quality and HIT, and average Augmented Clinical HIT and communication quality of hospitals located within a health referral region (HRR) are used as instruments for communication quality and HIT. 500 bootstrap replications were performed. All regressions were run with year fixed effects. Predicted residuals from the first stage are added as controls. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

transformation to the score. Specifically, the communication quality score, $S_{i,t}$, for hospital i and time period t with percentage score $Q_{i,t}$ is given by:

$$S_{i,t} = Ln\left[\frac{Qi,t}{1 - Qi,t}\right]$$

The results when using the alternate measure of communication quality are presented in Table 8 and remain consistent with the main analysis.

Finally, although we control for intermediate quality of care measures—e.g., conformance quality and LOS, it is possible that end quality of care measures—

Table 9 Instrumental Variable Fractional Response Model with Bootstrapped Standard Errors to Determine Effect of HIT, Communication, and Their Interaction on Adjusted Lawsuits with Readmissions Rate as an Additional Control

	Readmissions rate added as control		
	Coeff.	SE	95% CI
Communication quality	−0.003	0.009	(−0.021, 0.014)
HIT	−0.040*	0.022	(−0.084, 0.003)
Communication quality × HIT	−0.011**	0.005	(−0.020, −0.001)
Constant	−2.937***	0.494	(−3.907, −1.967)
Readmissions rate	−0.005	0.023	(−0.050, 0.039)
Case mix index	−0.347**	0.166	(−0.674, −0.021)
Wage index	0.358	0.720	(−1.054, 1.770)
Number of beds	−0.0003**	0.0002	(−0.0007, −0.0000)
Length of stay	−0.110**	0.045	(−0.200, −0.020)
Resident to bed ratio	0.440	0.483	(−0.508, 1.388)
Conformance quality	−0.032	0.026	(−0.083, 0.018)
Population density	0.000	0.000	(−0.000, 0.000)
Non-augmented clinical HIT	0.019**	0.008	(0.003, 0.036)
Law firm concentration	−0.003	0.027	(−0.056, 0.049)
Hospital reputation	−0.006	0.131	(−0.264, 0.250)
Pseudo R^2		0.04	
p-value		0.00	
Observations		548	

Notes: "HIT" is our hypothesized technology variable of interest, Non-augmented clinical HIT is a control variable. Lagged values of communication quality and HIT, and average Augmented Clinical HIT and communication quality of hospitals located within a health referral region (HRR) are used as instruments for communication quality and HIT. Here 500 bootstrap replications were performed. All regressions were run with year fixed effects. Predicted residuals from the first stage are added as controls. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

e.g., readmissions rate, have a stronger impact in influencing lawsuits. Consequently, as a robustness check, we control for the 30 day readmissions rate for a hospital when evaluating the impact of communication quality and HIT on lawsuits. We obtain the 30-day readmissions rate for a hospital from the CMS process of care database. CMS reports 30-day readmissions rate for heart attack, heart failure and pneumonia. The readmissions rate for a hospital is calculated as a weighted average for these three conditions. The results using the alternate measure of quality of care using an instrumental variable fractional response model with bootstrapped standard errors are presented in Table 9 and remain consistent with the main analysis.

8. Discussion

Our results support a significant and direct relationship between HIT adoption and fewer lawsuits filed, which becomes stronger for hospitals with higher communication quality scores. We explain that higher levels of HIT coupled with good communication enables operational transparency, which has been shown to improve customer perceptions of service quality. Past work has applied operational transparency to food service, self-service technology, and government services (Buell and Norton 2011, Buell et al. 2017, 2018). While this previous work uses technology to demonstrate operational transparency (for example, an aggregator website displays the various websites searched to find the best price for an airline flight), we flip this approach and use people to demonstrate operational transparency (interpreting and explaining what has been done, as displayed by the HIT systems). In other words, we extend operational transparency to complex service operations, where communication acts as a bridge between technology and the end customer (patient). Because of the complexity and highly technical nature of health care information, which necessitates interpretation and effective communication by a care provider, the personal communication of healthcare providers acts as a bridge to provide operational transparency.

This operational transparency created through the interaction of HIT and communication quality also sheds light on the inconclusive relationship between HIT and malpractice lawsuits previously found in the literature. It is possible that the positive (Quinn et al. 2012), insignificant (Virapongse et al. 2008), and negative (Miller and Tucker 2014) impact of HIT reported in the literature may be due to failing to account for factors like communication quality in their study samples. Our analysis shows that communication quality will impact how HIT influences number of lawsuits.

Although previous research has concluded there is a relationship between better communication and fewer lawsuits, much of this literature does not account for technology within the environment. We did not posit any direct relationship between communication quality and lawsuits, but we note Table 2 shows no direct, significant relationship between the two constructs. This insignificance could be due to how communication influences an interactive effect as opposed to direct effect, once technology is considered within the model, and should be investigated in future research.

As hospitals tend to operate with narrow margins, it is important to understand the payoff of operational investments. Hospitals are investing heavily in HIT and communication to both improve quality, and to increase reimbursements as a result of the ACA legislation. In addition to these primary reasons for HIT investment, hospitals can also reap the secondary benefit of lawsuit reduction. However, hospitals can receive more benefits when they couple improved communication and HIT together. As indicated by our results, an average hospital can annually save approximately $833,032 in lawsuit costs by investing in HIT and improved communication quality. However, this same hospital could lose as much as \$541,976 in additional lawsuit costs if investments in HIT are made without corresponding improvements in communication quality. Our analysis provides evidence that an investment in HIT without improvements to communication will have less of an impact on reducing lawsuits than improving both HIT and communication together. Thus, understanding the implications of these interactions is important for operations decision makers in hospitals and health systems.

We also find significant heterogeneity in this relationship based on the level of HIT, with positive synergies between HIT and communication (at medium to high levels) in reducing lawsuits being stronger in early cycles of HIT adoption. On the other hand, the observed increase in lawsuits at low communication levels become stronger as the HIT adoption at a hospital increases. Given the trend towards increased HIT adoption hospitals should take steps to achieve at least a reasonable level of communication quality in order to minimize additional expenses as a result of increased lawsuits.

We also find that the relationship between HIT and lawsuits remains consistent irrespective of the stakeholder involved in communication (physician or nurse). This result emphasizes the need to focus on improving communication quality for all caregivers. While hospitals recognize the need for communication training (Levinson et al. 2010, Weir 2012), there are often barriers to improving communication. Physicians generally are severely time constrained (Koven 2012, Weir 2012), thus limiting physicians' ability to communicate well. Additionally, communication patterns within hospitals tend to be reinforced by the overall culture of the hospital (Dutta et al. 2017, Levinson et al. 2010). This aligns with the anthropology literature, which explains that culture influences communication within an organization, and then as individuals communicate, they reinforce the cultural norm (Schall 1983). We mention this to say that improving communication requires a larger effort than one-time training.

Finally, one might surmise that the mechanisms for affecting patients' perceptions might differ for low severity vs. high severity injuries. Our results indicate that this is not the case. That is, HIT and communication have an effect on the number of both severe and non-severe lawsuits. This result indicates the importance of operational transparency in reducing lawsuits, irrespective of the severity of injury resulting in the lawsuit.

Besides these operational implications, we also provide rigorous testing, including multiple robustness checks, addressing endogeneity using different sets of instruments, demonstrating validity of results across different model specifications and operationalization of key variables. This rigorous testing builds on and strengthens the original HIT-lawsuit research.

9. Limitations and Conclusions

We acknowledge the following limitations in our study. First, our measure of communication quality is based on the HCAHPS survey conducted by CMS and may not accurately capture all forms of caregiver–patient interactions. Second, although we control for many hospital-level characteristics, we are unable to account for caregiver-level factors that may influence lawsuits filed through quality issues. Third, our measure of HIT levels is based on an index created based on the presence of individual HIT. This index may not provide an accurate measure of the actual usage of HIT at a hospital. Finally, we only study the impact of augmented clinical HIT and its interaction with communication quality on lawsuits. We acknowledge that there are other types of HITs in the hospital environment—clinical HITs (involved in patient data collection and diagnosis) and administrative HITs (involved in administrative data flow within the hospital). Although we control for these HITs in our analysis, it is possible that interactions between these HITs and hospital environmental variables yield new insights regarding lawsuits. Future research should attempt to mitigate the above limitations and help further advance our understanding of drivers behind malpractice lawsuits. Even with the above limitations, we are confident in the accuracy of our findings, given their strong theoretical foundation as well as support through multiple robustness checks.

Our analysis helps us to understand how HIT, meant to improve quality, can either enhance or detract from a patient's experience, depending on how care providers integrate HIT into their care routines. By undertaking rigorous analysis of this phenomenon, along with estimated cost savings, we better understand the impact of HIT adoption, and more importantly, how the environment (specifically communication environment) shifts the benefit of HIT adoption. This allows for a better understanding of the integrated nature of tools and environment.

By taking this approach, we fill important gaps in the medical malpractice lawsuits process literature. Supporting the existing literature, we show that higher HIT maturity is associated with reduced lawsuits. Additionally, we find that communication quality complements HIT in reducing lawsuits. These contributions help further our understanding of the drivers behind malpractice lawsuits as well as the operational mechanisms to mitigate their occurrence.

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References

Abrahamson, E., L. Rosenkopf. 1993. Institutional and competitive bandwagons: Using mathematical modeling as a tool to explore innovation diffusion. *Acad. Manag. Rev.* **18**(3): 487–517.

Altarum Institute. 2011. *Overcoming Challenges to Health IT Adoption in Small, Rural Hospitals*. Author, Ann Arbor, MI.

Anderson, J. C., D. W. Gerbing. 1988. Structural equation modeling in practice: A review and recommended two-step approach. *Psychol. Bull.* **103**(3): 411–423.

Angst, C. M., R. Agarwal, V. Sambamurthy, K. Kelley. 2010. Social contagion and information technology diffusion: The adoption of electronic medical records in U.S. hospitals. *Management Sci.* **56**(8): 1219–1241. https://doi.org/DOI 10.1287/mnsc.1100.1183.

Angst, C. M., S. Devaraj, J. D'Arcy. 2012. Dual role of IT-assisted communication in patient care: A validated structure-process-outcome framework. *J. Manage. Inf. Sys.* **29**(2): 257–292.

Appari, A., E. K. Carian, M. E. Johnson, D. L. Anthony. 2012. Medication administration quality and health information technology: A national study of US hospitals. *J. Am. Med. Inform. Assoc.* **19**(3): 360–367.

Appari, A., M. E. Johnson, D. L. Anthony. 2013. Meaningful use of electronic health record systems and process quality of care: Evidence from a panel data analysis of US acute-care hospitals. *Health Serv. Res.* **48**(2pt1): 354–375.

Arabmazar, A., P. Schmidt. 1981. Further evidence on the robustness of the Tobit estimator to heteroskedasticity. *J. Econom.* **17**(2): 253–258.

Arellano, M., S. Bond. 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Rev. Econ. Stud.* **58**(2): 277–297.

Ashby, J., S. Guterman, T. Greene. 2000. An analysis of hospital productivity and product change. *Health Aff.* **19**(5): 197–205.

Bal, B. S. 2009. An introduction to medical malpractice in the United States. *Clin. Orthop. Relat. Res.* **467**(2): 339–347.

Barlas, S. 2011. Hospitals scramble to meet deadlines for adopting electronic health records. *Pharm. Ther.* **36**(1): 37–40.

Bates, D. W., A. A. Gawande. 2003. Improving safety with information technology. *N. Engl. J. Med.* **348**(25): 2526–2534.

Bhattacharyya, T. 2005. Evidence-based approaches to minimizing malpractice risk in orthopedic surgery. *Orthopedics* **28**(4): 378–381.

Bloom, N., J. Van Reenen. 2007. Measuring and explaining management practices across firms and countries. *Quart. J. Econ.* **122**(4): 1351–1408.

Boyer, K. 1999. Evolutionary patterns of flexible automation and performance: A longitudinal study. *Management Sci.* **45**(6): 824–842.

Buell, R. W., M. I. Norton. 2011. The labor illusion: How operational transparency increases perceived value. *Management Sci.* **57**(9): 1564–1579.

Buell, R. W., T. Kim, C. J. Tsay. 2017. Creating reciprocal value through operational transparency. *Management Sci.* **63**(6): 1673–1695.

Buell, R. W., E. Porter, M. I. Norton. 2018. Surfacing the submerged state: Operational transparency increases trust in and engagement with government. Harvard Business School Working Paper, No. 14-034, September 2016. Harvard Business School Technology & Operations Mgt. Unit Working Paper No 14-034. Available at SSRN: https://ssrn.com/abstract=2349801.

Buntin, M. B., S. H. Jain, D. Blumenthal. 2010. Health information technology: Laying the infrastructure for national health reform. *Health Aff.* **29**(6): 1214–1219.

Chandrasekaran, A., C. Senot, K. K. Boyer. 2012. Process management impact on clinical and experiential quality: Managing tensions between safe and patient-centered healthcare. *Manuf. Serv. Oper. Manag.* **14**(4): 548–566.

Chaudhry, B., J. Wang, S. Wu, M. Maglione, W. Mojica, E. Roth, S. C. Morton, P. G. Shekelle. 2006. Systematic review: Impact of health information technology on quality, efficiency, and costs of medical care. *Ann. Intern. Med.* **144**(10): 742–752.

Chen, C. X., E. M. Matsumura, J. Y. Shin, S. Y.-C. Wu. 2015. The effect of competition intensity and competition type on the use of customer satisfaction measures in executive annual bonus contracts. *Account. Rev.* **90**(1): 229–263.

Collett, D. 2003. *Modeling Binary Data*. CRC Press, Boca Raton, FL.

Core, J. E., W. Guay, D. F. Larcker. 2008. The power of the pen and executive compensation. *J. Financ. Econ.* **88**(1): 1–25.

Duke, P., R. Frankel, S. Reis. 2013. How to integrate the electronic health record and patient-centered communication into the medical visit: A skills-based approach. *Teach. Learn. Med.* **25**(4): 358–365.

Dutta, S., F. Fullam, J. Behel. 2017. How we improved hospitalist-patient communication. *NEJM Catalyst*. February 5.

Ettlie, J. E. 1983. Organizational policy and innovation among suppliers to the food processing sector. *Acad. Manag. J.* **26**(1): 27–44.

Frankel, R., A. Altschuler, S. George, J. Kinsman, H. Jimison, N. R. Robertson, J. Hsu. 2005. Effects of exam-room computing on clinician–patient communication. *J. Gen. Intern. Med.* **20**(8): 677–682.

Galbraith, J. 1977. *Organization Design*. Addison-Wesley, Reading, MA.

Gallani, S., R. Krishnan, J. M. Wooldridge. 2015. *Applications of Fractional Response Model to the Study of Bounded Dependent Variables in Accounting Research*. Working Paper 16-016. Harvard Business School Accounting & Management Unit.

Gardner, J. W., K. K. Boyer, J. V. Gray. 2015. Operational and strategic information processing: Complementing healthcare IT infrastructure. *J. Oper. Manag.* **33**: 123–139.

Glick, H. A., S. M. Orzol, J. F. Tooley, J. O. Mauskopf. 2003. Design and analysis of unit cost estimation studies: How many hospital diagnoses? How many countries? *Health Econ.* **12**(7): 517–527.

Glouberman, S., H. Mintzberg. 2001. Managing the care of health and the cure of disease—Part I: differentiation. *Health Care Manage. Rev.* **26**(1): 56–69.

Grosskopf, S., D. Margaritis, V. Valdmanis. 2001. The effects of teaching on hospital productivity. *Socio-Econ. Plann. Sci.* **35**(3): 189–204.

Handley, S. M. 2017. How governance misalignment and outsourcing capability impact performance. *Prod. Oper. Manag.* **26**(1): 134–155.

Hastie, T., R. Tibshirani, J. Friedman. 2009. *Linear Methods for Regression*. Springer, New York.

Henry, J., Y. Pylypchuk, T. Searcy, V. Patel. 2016. Adoption of electronic health record systems among US non-federal acute care hospitals: 2008–2015. ONC Data Brief, No. 35. Office of the National Coordinator for Health Information Technology: Washington, DC.

Holman, M., N. Vidmar, P. Lee. 2011. Most claims settle: Implications for alternative dispute resolution from a profile of medical-malpractice claims in Florida. *Law Contemp. Probl.* **74**(3): 103–133.

Jones, S. S., R. S. Rudin, T. Perry, P. G. Shekelle. 2014. Health information technology: An updated systematic review with a focus on meaningful use. *Ann. Intern. Med.* **160**(1): 48–54.

Kesavan, S., B. R. Staats, W. Gilland. 2014. Volume flexibility in services: The costs and benefits of flexible labor resources. *Management Sci.* **60**(8): 1884–1906.

Kohli, R., S. Devaraj. 2004. Realizing the business value of information technology investments: An organizational process. *MIS Q. Exec.* **3**(1): 53–68.

Koven, S. 2012. The difference between doctors and nurses. *Boston Globe*, October 22.

Levinson, W., D. L. Roter, J. P. Mullooly, V. T. Dull, R. M. Frankel. 1997. Physician-patient communication: The relationship with malpractice claims among primary care physicians and surgeons. *JAMA* **277**(7): 553–559.

Levinson, W., C. S. Lesser, R. M. Epstein. 2010. Developing physician communication skills for patient-centered care. *Health Aff.* **29**(7): 1310–1318.

Lin, W., J. M. Wooldridge. 2017. Binary and fractional response models with continuous and binary endogenous explanatory variables. Working paper, available at http://www.weilinmetrics.com/uploads/5/1/4/0/51404393/chap1_20180405_jmw_wl.pdf (accessed date March 2019).

Mangalmurti, S. S., L. Murtagh, M. M. Mello. 2010. Medical malpractice liability in the age of electronic health records. *N. Engl. J. Med.* **363**(21): 2060–2067.

Mate, K. S., A. L. Compton-Phillips. 2014. The antidote to fragmented health care. *Harvard Business Review Digital Articles*, 2–7.

McCullough, J. S., M. Casey, I. Moscovice, S. Prasad. 2010. The effect of health information technology on quality in US hospitals. *Health Aff.* **29**(4): 647–654.

McCullough, J. S., S. T. Parente, R. Town. 2016. Health information technology and patient outcomes: The role of information and labor coordination. *Rand J. Econ.* **47**(1): 207–236.

Mello, M. M., A. Chandra, A. A. Gawande, D. M. Studdert. 2010. National costs of the medical liability system. *Health Aff.* **29** (9): 1569–1577.

Menon, N. M., R. Kohli. 2013. Blunting Damocles' sword: A longitudinal model of healthcare IT impact on malpractice insurance premium and quality of patient care. *Inf. Syst. Res.* **24**(4): 918–932.

Menor, L. J., A. V. Roth. 2008. New service development competence and performance: An empirical investigation in retail banking. *Prod. Oper. Manag.* **17**(3): 267–284.

Milgrom, P., J. Roberts. 1995. Complementarities and fit strategy, structure, and organizational change in manufacturing. *J. Account. Econ.* **19**(2–3): 179–208.

Miller, A. R., C. E. Tucker. 2014. Electronic discovery and the adoption of information technology. *J Law Econ Organ* **30**(2): 217–243.

Nagar, V., M. V. Rajan. 2005. Measuring customer relationships: The case of the retail banking industry. *Management Sci.* **51**(6): 904–919.

Papke, L. E., J. M. Wooldridge. 1996. Econometric methods for fractional response variables with an application to 401(k) plan participation rates. *J. Appl. Econ.* **11**: 619–632.

Papke, L. E., J. M. Wooldridge. 2008. Panel data methods for fractional response variables with an application to test pass rates. *J. Econom.* **145**(1–2): 121–133.

Porter, M. E. 2010. What is value in health care? *N. Engl. J. Med.* **363**(26): 2477–2481.

Queenan, C. C., C. M. Angst, S. Devaraj. 2011. Doctors' orders—If they're electronic, do they improve patient satisfaction? A complements/substitutes perspective. *J. Oper. Manag.* **29**(7): 639–649.

Quinn, M. A., A. M. Kats, K. Kleinman, D. W. Bates, S. R. Simon. 2012. The relationship between electronic health records and malpractice claims. *Arch. Intern. Med.* **172**(15): 1187–1189.

Ransbotham, S., E. M. Overby, M. C. Jernigan. 2016. Electronic trace data and legal outcomes: The effect of electronic medical records on malpractice claim resolution time. Georgia Tech Scheller College of Business Research Paper No. 2016-052.

Ratanawongsa, N., J. L. Barton, C. R. Lyles, M. Wu, E. H. Yelin, D. Martinez, D. Schillinger. 2016. Association between clinician computer use and communication with patients in safety-net clinics. *JAMA Intern. Med.* **176**(1): 125–128.

Rathert, C., J. N. Mittler, S. Banerjee, J. McDaniel. 2016. Patient-centered communication in the era of electronic health records: What does the evidence say? *Patient Educ. Couns.* **100** (1): 50–64.

Ridker, R. G., J. A. Henning. 1967. The determinants of residential property values with special reference to air pollution. *Rev. Econ. Stat.* **49**(2): 246–257.

Rigobon, R., T. M. Stoker. 2007. Estimation with censored regressors: Basic issues. *Int. Econ. Rev.* **48**(4): 1441–1467.

Schall, M. S. 1983. A communication-rules approach to organizational culture. *Adm. Sci. Q.* **28**(4): 557–581.

Schleiter, K. E. 2009. Difficult patient-physician relationships and the risk of medical malpractice litigation. *Virtual Mentor* **11**(3): 242.

Seabury, S. A., A. Chandra, D. N. Lakdawalla, A. B. Jena. 2013. On average, physicians spend nearly 11 percent of their 40-year careers with an open, unresolved malpractice claim. *Health Aff.* **32**(1): 111–119.

Senot, C., A. Chandrasekaran, P. T. Ward, A. L. Tucker, S. D. Moffatt-Bruce. 2015. The impact of combining conformance and experiential quality on hospitals' readmissions and cost performance. *Management Sci.* **62**(3): 829–848.

Shachak, A., S. Reis. 2009. The impact of electronic medical records on patient–doctor communication during consultation: A narrative literature review. *J. Eval. Clin. Pract.* **15**(4): 641–649.

Sharma, L., A. Chandrasekaran, K. K. Boyer, C. M. McDermott. 2016. The impact of health information technology bundles on hospital performance: An econometric study. *J. Oper. Manag.* **41**: 25–41.

Siebert, W. S., N. Zubanov. 2010. Management economics in a large retail company. *Management Sci.* **56**(8): 1398–1414.

Sine, W. D., S. Shane, D. D. Gregorio. 2003. The halo effect and technology licensing: The influence of institutional prestige on the licensing of university inventions. *Management Sci.* **49**(4): 478–496.

Spetz, J., L. S. Maiuro. 2004. Measuring levels of technology in hospitals. *Q. Rev. Econ. Financ.* **44**(3): 430–447.

Staiger, D. O., J. H. Stock. 1994. Instrumental variables regression with weak instruments. *Econometrica* **65**(3): 557–586.

Stewart, M. A. 1995. Effective physician-patient communication and health outcomes: A review. *CMAJ. Can. Med. Assoc. J.* **152** (9): 1423.

Tan, T. F., S. Netessine. 2014. When does the devil make work? An empirical study of the impact of workload on worker productivity. *Management Sci.* **60**(6): 1574–1593.

Taylor, J. B. 2005. Relationships among patient age, diagnosis, hospital type, and clinical laboratory utilization. *Clin. Lab. Sci.* **18**(1): 8.

Theokary, C., Z. J. Ren. 2011. An empirical study of the relations between hospital volume, teaching status, and service quality. *Prod. Oper. Manag.* **20**(3): 303–318.

Thomas, J. W., K. E. Guire, G. Horvat. 1997. Is patient length of stay related to quality of care? *Hosp. Health Serv. Adm.* **42**(4): 489–507.

Victoroff, M. S., B. M. Drury, E. J. Campagna, E. H. Morrato. 2013. Impact of electronic health records on malpractice claims in a sample of physician offices in Colorado: A retrospective cohort study. *J. Gen. Intern. Med.* **28**(5): 637–644.

Virapongse, A., D. W. Bates, P. Shi, C. A. Jenter, L. A. Volk, K. Kleinman, L. Sato, S. R. Simon. 2008. Electronic health records and malpractice claims in office practice. *Arch. Intern. Med.* **168**(21): 2362–2367.

Weir, K. 2012. Improving patient-physician communication. *Monit. Psychol.* **43**(10): 36.

Wooldridge, J. M. 2002. *Econometric Analysis of Cross Section and Panel Data*. MIT Press, Cambridge, MA.

Wooldridge, J. M. 2015. Control function methods in applied econometrics. *J. Hum. Resour.* **50**(2): 420–445.

Supporting Information

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

Figure A1: The Confirmatory Factor Analysis (CFA) Model for Communication Quality.

Table A1: Instrumental Variable Fractional Response Model with Bootstrapped Standard Errors to Determine Effect of HIT, Communication, and Their Interaction on Adjusted Lawsuits Using Alternate Instrumental Variables.

Table A2: First Stage Regression Models for HIT and Communication Quality.

Table A3: Instrumental Variable Random Effects Fractional Response Model with Bootstrapped Standard Errors to Determine Effect of HIT, Communication, and Their Interaction on Adjusted Lawsuits.

Table A4: Fractional Response Model to Determine Effect of HIT, Communication Quality, and Their Interaction on Adjusted Lawsuits (without accounting for endogeneity).

Table A5: Test for Instrument Validity Using a Fractional Response Model Using Instruments as Predictors.