INVESTIGATING ECONOMIC, DESIGN, AND USABILITY ASPECTS OF ELECTRONIC HEALTH RECORD SYSTEMS

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Abstract: Following a 3-essay approach, this dissertation explores three aspects of healthcare IT using three different methodologies. In the first essay, we use econometric modeling to quantify the business value of information exchange using spillover mechanisms and discuss its implications in propagating sustained collaboration between ambulatory and tertiary care. Leveraging a nationwide sample of 3,483 US hospitals across 13 years, matched with approximately 30,000 ambulatory care facilities, we find that focal hospitals' inpatient cost per discharge decreases as EMR adoption by neighboring ambulatory facilities increases. Further, these effects are more substantial for urban, densely populated regions with more ambulatory entities that are proximal. This represents the bright side of EHR use. Next, the second essay uses a qualitative approach to understand the unintended consequences or dark side of EHR use. In this study, we interviewed 24 physicians across 11 specialties to understand what specific EHR characteristics cause stress among physicians. Following the standard qualitative coding process, we identify fifty-one design issues and ten stress-inducing EHR design themes that provide a deeper understanding of the technostress phenomenon. In addition, our findings can be used by EHR vendors to design better information systems. The final and third essay contributes to the lack of usability testing models and presents a proof of concept EHR usability evaluation model based on discrete event simulation techniques. Using literature-based workflow sequence and time-motion data assumptions, we show how to use simulation techniques to evaluate whether an EHR system delivers operational value in physician utilization. Usability evaluation is the first step in designing better EHR systems, and thus our proof-of-concept model can be used by EHR vendors and certification authorities to appraise the operational value of EHR applications. Overall, this dissertation investigates- 1) the bright side of EHR use that generates economic value for its users; 2) the dark side of EHR use that provides a deeper understanding of the physician burnout problem; 3) provides a solution that helps in designing better EHR systems while mitigating its unintended consequences.

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CHAPTER I

OVERVIEW

Interoperable electronic health records (EHR) are touted as the most promising solution to address the fragmented care delivery in the United States. By 2018, almost 96% of hospitals and 85% of physician offices have successfully adopted EHR systems, however, participation in information exchange is still lagging behind at 40% (Bates and Samal 2018). Unsustainable business model is identified as the biggest roadblock surrounding decline in health information exchange (HIE) participation (Adler-Milstein et al. 2016). Further, anecdotal evidence has expressed providers' concern over losing competitive advantage. In this light, the first essay of this dissertation, use network externalities to quantify the business value of EHR-driven regional information exchange that can motivate providers to move from a 'competitive advantage' to a 'sustainable collaboration' mindset.

On the user side, mandatory use of inefficient EHR systems has forced physicians to work outside of their regular working hours (Adler-Milstein et al. 2020). The 2018 Physician Foundation Survey found that EHR are the greatest source of professional dissatisfaction among physicians and that 29% of the physician's plan to quit practicing medicine. The burgeoning problem of physician burnout can cost US$ 4.6 Billion annually (Han et al. 2019) offsetting the economic gains from HIT reform (Tarafdar et al. 2007). EHR-driven stress among physicians is a complex problem that necessitates research into the EHR design characteristics that manifests as stressors and impact its usability. Thus, the second essay qualitatively explores specific EHR design characteristics that cause stress among physicians.

Further, it is noted that usability evaluation of EHR's is not standardized and needs the attention of academic researchers in order to devise objective evaluation methods that uses quantitative data such as number of clicks, time to complete tasks, and error rates (McDonnell et al. 2010). The operations and workflow perspective of EHR usability can help vendors design and develop better systems. A recent call suggests the use of simulation techniques to replace expensive and time-consuming survey and observational methods of usability evaluation (Guo et al. 2020). Thus, the third essay builds upon this gap and presents a proof of concept that is capable of objectively evaluating the usability of EHR systems using simulation techniques.

Following a 3-essay approach, this dissertation investigates how does information technology impacts firms and individuals. It is essential within the overall healthcare delivery landscape given the increasing dependency on IT systems in conjunction with the federal mandate to use electronic health records (EHR) systems. Broadly, this dissertation investigates three facets of healthcare IT: First, the bright side is the economic value that IT use brings to firms by improving financial and clinical outcomes. Second, the dark side or unintended consequence is the forced dependency on poorly designed EHR systems, causing stress among physicians and nurses. Finally, my third essay closes the loop by developing a simulation-based proof-of-concept that objectively evaluates the usability of EHR systems. The results of the second and third essay can be used to design and develop better EHR systems. Overall, my dissertation aims to utilize multiple methods and theoretical lenses to provide evidence and insights that facilitate IT success in healthcare through sustainable collaboration among providers and appraising EHR systems' design and usability. Below, I briefly summarize my current work and outline future research plans. A short summary for each of the three essays is presented below:

Essay 1: Electronic Health Record Spillovers and Sustainable Cooperation

An unsustainable business model is identified as the biggest roadblock surrounding declining participation in health information exchange (HIE). Further, anecdotal evidence has expressed providers' concern over losing competitive advantage. On the flip side, research has shown that sharing health information can help providers improve health outcomes. We argue that the tension between business and health outcomes can be reconciled with empirical evidence that quantifies the business value of sustained cooperation among healthcare providers. Further, we note that the patient and information exchange between ambulatory care clinics and tertiary care hospitals and vice versa (between referrals) is an understudied phenomenon compared to inter-hospital transfers (within referrals) or primary to specialty referrals (within referrals). Hence, our main research question is "what is the economic impact of EHR adoption of neighboring ambulatory care facilities (clinics, diagnostic facilities, rehabilitation centers, and urgent care) on the inpatient cost of a focal hospital in a hospital referral region (HRR)?"

Grounded in the network externalities embedded within inter-organizational systems (IOS), we hypothesize that higher EHR adoption of neighboring ambulatory care facilities is associated with lower hospital inpatient costs per discharge. We test our research model through balanced panel analyses of data from 2005 to 2017, including 45,279 hospital-year observations from 3,483 hospitals matched with an average of 30,000 ambulatory care facilities across the United States. Our results show significant effects of IT adoption by regional ambulatory care facilities on hospital inpatient cost per discharge. Furthermore, these effects are enhanced in geographic agglomerations like urban areas, highly populated areas, areas with better access to health services, and when ambulatory entities and hospitals belong to the same hospital system. In summary, our results add to the extant knowledge about the business value of HIT adoption. Our proposed referral network model and empirical evidence on significant regional level network effects can motivate providers to move from a ‘competitive advantage’ to a ‘sustainable collaboration’ mindset and thus engage more in health information exchange activities.

Essay 2: Technostress Among Physicians: Conceptualizing Stressful EHR Design Features

Mandatory use of inefficient EHR systems has forced physicians to work outside of their regular working hours, causing professional dissatisfaction. In addition, the burgeoning problem of physician burnout can offset the economic gains from HIT reform as clinicians plan to retire, change careers, or reduce working hours. EHR-driven stress among physicians is a complex problem requiring research into the EHR design characteristics that manifest as stressors and impact its usability. Technostress literature has identified why users feel stressed; however, we have limited to no information about what aspects of IS design are stressful. We address this gap by qualitatively exploring our main research question, “what specific EHR characteristics cause stress among its users?” Drawing on the theoretical foundations of the technostress phenomenon, we present a context-specific conceptualization of information system design features and themes that afford stress among healthcare users.

In this study, we interviewed twenty-four physicians across eleven sub-specialties to understand EHR characteristics that cause stress among physicians. Leveraging the first-hand information from physicians and following a structured qualitative coding process, we identify fifty-one design issues, from which ten EHR-design themes have emerged. Our results provide a deeper understanding of the technostress phenomenon with significant practical and theoretical implications. Most importantly, despite physicians being the central actors in the care delivery model, electronic health record design does not consider specialty-specific workflow. Furthermore, physicians’ concerns related to the validity of EHR data is also be a source of their stress. Overall, for successful digital transformation in healthcare, we need to design EHR systems that work in favor of their key users, while minimizing its unintended consequences.

Notably, this is the first research that explores stressful IS design aspects within a contextual healthcare environment. By doing so, we can inform practitioners on how to design and develop better information systems that mitigate the unintended consequences of EHR use.

Essay 3: Simulation-Based EHR Usability Evaluation: A Proof of Concept

Poor usability of EHR solutions is directly associated with physician burnout. We identify and describe this problem in Essay 2 and further note that usability evaluation of EHR's is not standardized and needs objective evaluation using methods that use quantitative data such as the number of clicks, time to complete tasks, and error rates. Evaluating EHR usability from the perspective of operations and workflow can help vendors design and develop better systems. In addition, this work addresses a recent call that suggests using simulation techniques to replace expensive and time-consuming survey and observational usability evaluation methods. While subjective methods have been utilized widely in the usability evaluation of EHR's, it does not seem to be helping with the continuous improvement of EHR design and user satisfaction. We address this gap by presenting a proof of concept that can objectively evaluate the usability of EHR systems using discrete event system simulation.

We are currently collecting task-time data published in physician workflow/ time-motion studies to approximate the task distributions. Based on task distributions and standard simulation model development methodology, we can build simulation models for different specialty-specific EHR workflows that imitates the operation of a real-world process over time. In Essay 3, we present an example workflow of an emergency department, data collection format, and a proof-of-concept simulation model with assumed task-time distributions. The simulation model results in terms of clinic efficiency and resource (clinician) utilization metrics can serve as a proxy to evaluate the usability of the information systems.

This proof of concept is aimed to pave the road towards a more comprehensive simulation-based quantitative models to understand and improve EHR usability. First, we expect our results to open a new avenue for objective evaluation of EHR usability that determines if an EHR system can deliver operational value or not. Second, simulation-based usability evaluation can augment time-motion-based pre-post or survey-based evaluation methods that are expensive and time-consuming. Finally, considering the increasing popularity of digital health solutions and IoT in healthcare, this method can also evaluate the usability of other digital health solutions. Again, this work represents one of the very few studies that utilize simulation techniques for usability evaluation.

Overall, the purpose of this dissertation is to address the economic, design and usability aspects of EHR use wherein the first essay empirically shows that regional health information exchange generates business value, second essay unravels EHR-design features that manifest as stressors and the third essay present a novel EHR usability evaluation model that can help design better EHR systems.

CHAPTER II

ESSAY 1: ELECTRONIC HEALTH RECORD SPILLOVERS AND SUSTAINABLE COOPERATION

Introduction

The federal government is earnestly promoting the electronic exchange of health information, yet most healthcare providers think that the business model surrounding the health information exchange (HIE) efforts is not sustainable (Adler-Milstein et al. 2016). Specifically, hospitals are at risk of their competitors using the exchanged patient information to poach patients and gain insights into their operations and strategy, consequently losing competitive advantage (Adjerid et al. 2018). This may motivate providers to share patients internally within their health system or engage in information blocking practices (Everson et al. 2021; Miller and Tucker 2014).

Whereas prior research has shown that sharing health information can help improve health outcomes (Ayabakan et al. 2017a; Bao and Bardhan 2018), this quality improvement effort is not rewarded under the prevalent fee-for-service model. As a result, providers are reluctant to use HIE applications to overcome costly transaction barriers for interorganizational information sharing. Therefore, under the concurrent transition to a value-based care model, it is imperative to examine empirical evidence on the business value of sustained cooperation. In this work, we use referral networks to explore the economic value of ‘sustained cooperation among healthcare providers from the lens of network externalities arising from the adoption of electronic health records (EHR) and HIE applications.

EHR and HIE are interorganizational system (IOS) artifacts that facilitate electronic data interchange (EDI) and, in some cases, can integrate with other EHR systems. Most hospitals use EHR as the primary tool to exchange patient data with other providers outside their organizations (Johnson et al. 2018). Thus, EHR can create network externalities as it has the potential to facilitate clinical documentation, help manage and retrieve patient medical information, and communicate health records between providers. For instance, recent work by Atasoy et al. (2018 modeled EHR adoption externalities based on inter-hospital transfers and found that focal hospitals' operating costs decreases as more neighboring hospitals adopt EHRs.

While Atasoy et al. (2018 is an important first step in examining regional EHR spillover effects, we extend their work in two ways. First, inter-hospital transfers account for only 4% of hospital admissions (Hernandez-Boussard et al. 2017) and thus does not take into account EHR spillover effects due to approximately 26% of elective admissions (Ryan et al. 2010) wherein patient and information exchange occur between hospitals and ambulatory entities (primary care clinics and specialty physician offices). Second, Atasoy et al. (2018's EHR spillover model was restricted to the health service area (HSA) which are local healthcare markets with fewer hospitals located closer to each other, likely offering complementary services (Cutler and Scott Morton 2013). Thus, an EHR spillover model based on HSA may under-represent healthcare referral networks leading to possibly over-estimated spillover effects. This is because EHR spillover effects can accrue far beyond inter-hospital transfers with stronger effects in the case of geographically proximal firms (Orlando 2004).

Furthermore, prior literature primarily focused on performance implication of health IT in the same delivery level, and limited studies have empirically modeled the interaction between ambulatory entities and hospitals (Adler-Milstein et al. 2011; Chandrasekaran et al. 2021; Eftekhari et al. 2017; Yaraghi et al. 2015). Therefore, this work intends to enhance the current understanding of regional EHR spillover effects by assimilating how healthcare delivery is traditionally organized in primary, secondary, and tertiary care levels.

We present a healthcare *referral network model* that illustrates care delivery levels and the associated patient referral and information exchange. Thereupon, we model spillover effects of EHR adoption of ambulatory care entities on the inpatient cost of a focal hospital in a hospital referral region (HRR). In this work, ambulatory care entities are referred to as providers that offer outpatient care, such as primary and specialty outpatient clinics, diagnostic centers, rehabilitation centers, and urgent care centers. Our research model is grounded in the spillover phenomenon (Orlando 2004), and interorganizational systems (IOS) facilitated sustained cooperation in reciprocal networks (Kumar and Van Dissel 1996).

We test our research model using panel data from 2005 to 2017, including 3,483 hospitals and approximately 30,000 ambulatory entities across the United States. We find significant effects of EHR adoption by regional ambulatory care entities on inpatient cost per discharge of hospitals. The baseline results indicate that a 1% increase in the ambulatory EHR adoption in an HRR, on average, can reduce the inpatient cost per discharge of the focal hospital by 0.031% in one year and by 0.056% in four years. The reduction amounts to a saving of $51,000 per hospital per year and $93,000 per hospital over four years. Furthermore, savings are more salient for pharmacy and drug-related costs, urban areas with more ambulatory entities, and located proximally to the focal hospital. Most importantly, hospitals can save even if they share information with ambulatory entities outside their health system.

Our results contribute to the extant knowledge about the business value of information exchange grounded in regional network externalities between the understudied interface of ambulatory care entities and hospitals. Further, our empirical evidence on significant regional-level indirect effects on hospital costs can motivate healthcare providers to engage more in health information exchange activities, thus propagating a culture of sustained cooperation.

Theoretical Background and Related Literature

Sustainable Cooperation in Healthcare Referral Networks

We draw on WHO's Design and Implementation of Health Information Systems to develop a theoretical foundation for healthcare referral networks (Lippeveld et al. 2000). As shown in Figure 1 panel A, there are, in general three concentration levels of care based on their patient management functions. Primary care is the first point of contact between the provider and the population. The secondary level provides more specialized care like diagnostic and specialty outpatient services, while tertiary care provides highly specialized treatments such as surgical care and related interventions.

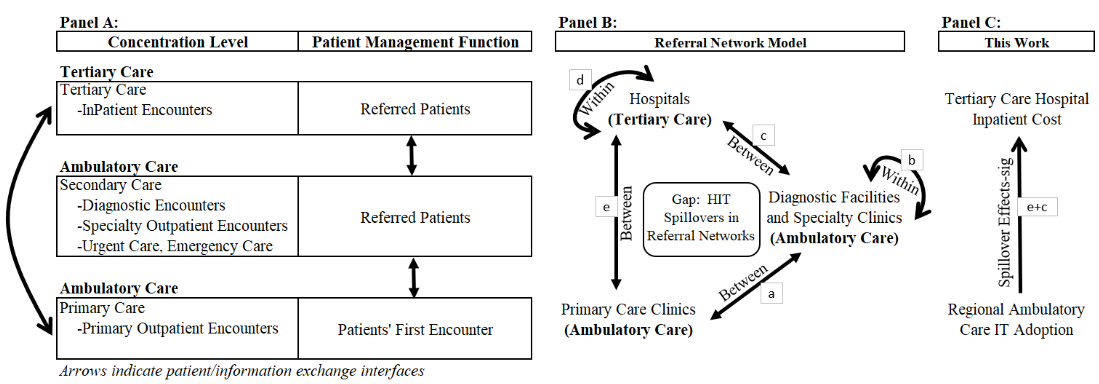
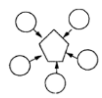
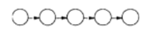
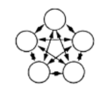


Figure 1: Conceptual and Theoretical Framework

We modified the WHO model per US healthcare and used a classification with two care levels – *ambulatory care* and *tertiary care*. Diagnostic entities, primary care clinics, and specialty outpatient clinics are classified as ambulatory care because they share similar workflow protocols, different from those in tertiary care hospitals. The amount of IT investment, the complexity of infrastructure, the adopted EHR systems, and organizational support are also different in ambulatory and tertiary settings, leading to heterogenous information sharing mechanism. (Chandrasekaran et al. 2021).

Table 1: A Typology of Interorganizational Systems (Kumar and van Dissel, 1996 and Volkoff et al. 1999)

Type of Interdependency	**Pooled**	**Sequential**	**Reciprocal**
Configuration			
Participants	-Competitors -Non-competitors	-Customers -Suppliers	-Partners, each providing a different specific advantage
Characteristics	-Shared Databases -Common communication networks -Common applications	-EDI- based orders -Order tracking -Database look-up	-Leverage complementary capabilities -Basic use of email, fax, voice communication -Advanced use of CAD/CASE data interchange and respositories -Integration technologies
Goal	-Economies of scale -Participation externalities	-Reduce cost, cycle time, and improve quality	-Temporary collaboration for specific products or services
Examples	-Insurance databases -ATM networks -Airline reservation systems -Travel agencies	EDI-based order and invoice system	-Video-conferencing Software **-Networked inter-organizational systems (IOS) -** EHR and HIE applications

We define *healthcare referral networks* as inter-related healthcare providers that cooperate for patient care reciprocally. Participants of healthcare referral networks are hospitals, primary care clinics, specialty care clinics, and diagnostic centers that play a specific role in patient care delivery (Figure 1 panel B). In the ideal scenario, they refer patients and provide coordinated care through health information sharing. Digitization of reciprocal interdependence necessitates the use of networked IOS such as EHR and HIE applications. Kumar and Van Dissel (1996 defined IOS as “the software and system manifestation of interorganizational relationships” and classified them based on three types of interdependencies – pooled, sequential, and reciprocal (Table 1). While IOS solutions for pooled (e.g., between providers and health insurance companies/payor) and sequential (e.g., between providers and drug/ consumables suppliers) interdependencies are mature, IT requirements for supporting the reciprocal dependencies are not defined, and the technology base supporting cooperation and interoperability is not well-developed.

Ideally, coordination cost reduces when interoperability is established for EHR and HIE, which leads to economic gains and fosters sustained cooperation among referral network participants (Clemons and Row 1992). However, in the absence of supporting evidence, cooperation among referral networks participants can easily degenerate into conflict (Volkoff et al. 1999). Unlike other industries, healthcare providers compete for patients and cooperate for care coordination. Their competition is mainly driven by referral network participants based on geographical proximities. The move from a competitive advantage (holding on to the patient information) to a cooperative advantage (sharing patient information) is an emerging phenomenon in healthcare to achieve the ideal scenario for value-based care. However, it needs empirical evidence on the economic value of cooperation in regional healthcare markets. Therefore, to realize the full potential of IOS, such as EHR and HIE, referral networks participants will need to shift their focus towards sustained cooperation.

Spillover Effects

Spillover refers to a phenomenon in which one party benefits from the actions of another party without incurring significant costs (Han et al. 2012). IT spillover refers explicitly to the impact of an aggregate pool of external IT investment on the growth and productivity of the focal firm after taking into account its own IT investment (Tambe and Hitt 2014). The concept of the aggregated pool of external investments is derived from the seminal work of Orlando (2004 that explains the importance of geographic and technological distance for interfirm spillovers. He found that distance proximity helps form agglomerations that improve firm productivity. Later, Zhu et al. (2006 examined how the network effects among firms influence the diffusion of the open standard system. Further, Cheng and Nault (2012 found that gains from IT investments in upstream industries may pass to downstream industries, as suppliers' improved products and demand forecasts also benefit their customers. With huge investments in healthcare IT, economic spillovers are of special interest to economists and policymakers as they help justify the policy decisions and stimulate growth (Tambe and Hitt 2014).

While the business value of healthcare information technology (HIT) is a rich body of literature (Collum et al. 2016; Eftekhari et al. 2017; Kohli et al. 2012; Menon et al. 2000; Wang et al. 2018), only recently have researchers explored spillover effects based on health information sharing or labor mobility (Atasoy et al. 2018; Freeman et al. 2021; Menon 2018). We extend this stream of literature by examining the spillover effects of regional ambulatory EHR adoption. We argue that information exchange occurs more in the referral interfaces involving ambulatory entities rather than in the case of inter-hospital transfers. In addition, primary care reforms are considered as a key to improving healthcare in the United States, with the Center for Medicare and Medicaid Innovation (CMMI) shifting focus from fee-for-service to population-based payment, suggesting a need for hospitals to better coordinate care and integrate with primary care (Horton 2019; Peikes et al. 2020). Thus, a holistic examination of referral networks can help researchers understand the indirect economic value generated through network externalities.

Research Hypothesis

Researchers have emphasized the importance of information exchange and its impact on the *continuity of care* (Kripalani et al. 2007). Bodenheimer (2008, in their provocative commentary on the perilous journey of a patient through the healthcare system, emphasizes the importance of coordinating care between primary care and other care levels. Figure 1 panel A shows that primary care and outpatient sub-specialties are ambulatory concerning their workflow. On the other hand, tertiary care hospitals provide specialized inpatient services and work with patients referred by primary care providers or previously seen by specialists in an outpatient setting. In addition, hospitals also solicit diagnostic test results from other ambulatory entities. Thus, an appropriate inpatient treatment plan needs medical information from multiple ambulatory care entities, as suggested by Figure 1 panel B. The adoption of EHR has helped these entities generate medical records in an electronic format that can be shared timely and conveniently.

EHR use can impact costs as they automate the clinical workflow and facilitate communication and coordination, yet its use increases the costs of the adopting focal hospital (Atasoy et al. 2019; Dranove et al. 2014). To this end, economic models examining indirect effects and complementarities have unraveled mechanisms that impact cost reduction (Adjerid et al. 2018; Atasoy et al. 2018). This is because EHR use facilitates care coordination within focal hospitals' departments and with disparate healthcare providers. In addition, improvements in quality, patient experience, and reduction in cost are rewarded under the hospital value-based purchasing program. Therefore, the routine interaction between hospitals and ambulatory entities is expected to bring down the cost of care for the focal hospital. Thus, our model is grounded in the cooperation among disparate participants of the referral network, and the cooperation will sustain if participants realize economic gains.

The patient referral and information exchange arrows in Figure 1 panel B illustrate provider types and coordination interfaces. We posit that each bidirectional interface (a, b, c, d, and e) in the referral network model will have spillover effects such that the focal entities will benefit from IT investment and adoption by neighboring entities in the healthcare market. We limit the scope of this paper to examine the spillover effects directed from ambulatory entities (primary/specialty clinics and diagnostic centers) to hospitals (i.e., interface c and e as indicated in Figure 1 panel C). Consequently, we hypothesize that as EHR adoption by ambulatory entities within an HRR increases over time, it will facilitate the timely exchange of information with tertiary care hospitals and thus help reduce inpatient costs. In other words, higher EHR adoption of neighboring ambulatory care entities is associated with lower hospital inpatient costs per discharge.

Data and Variable Construction

Patient referrals are usually made based on the geographical proximity of patients and healthcare services. Dartmouth Atlas defines HSA and HRR as regional healthcare markets where local hospitals meet the population's medical needs. There are 3,436 HSAs, and most contain only one hospital. However, HRRs are a larger agglomeration of zip codes with at least one hospital that provides advanced cardiovascular and neurosurgical procedures (Adjerid et al. 2018; Bao and Bardhan 2018; Wennberg and Cooper 1996). There is a total of 306 HRRs in the US. Thus, we use HRR as our geographic boundary because it captures even the last mile referral activity, which is the underlying spillover mechanism in our model.

We combined multiple data sources to form a multi-level panel. We collected granular data on EHR adoption for both ambulatory entities and hospitals from Healthcare Information and Management Systems Society (HIMSS) database, extensively used in HIT literature. The inpatient cost data and other hospital-level operational characteristics, such as the number of discharges and beds, are extracted from Medicare Cost Report (MCR). Case Mix Index is obtained from CMS Impact File while HRR to zip codes crosswalk data from Dartmouth Atlas. We further supplement it with HRR-level regional factors, such as average household income, from the 2010 US Decennial Census. We combined these datasets to construct a panel that consists of 3,483 hospitals and approximately 30,000 ambulatories entities from 2005 to 2017.

EHR Adoption

We followed Atasoy et al. (2018 and Dranove et al. (2014 to measure EHR adoption for hospitals and surrounding ambulatory entities. In the HIMSS database, hospitals report the adoption status of five commonly studied EHR applications, including Clinical Data Repository (CDR), Clinical Decision Support System (CDSS), Computerized Physician Order Entry (CPOE), Order Entry (OE), and Physician Documentation (PD). An application is adopted if the reported status is "Live and Operational" or "To Be Replaced".[1] We calculate Hospital EHR adoption as a ratio of adopted EHR applications to the total number of EHR applications (five applications). This variable ranges between zero and one, where one indicates that all EHR applications are adopted.

In the HIMSS database, ambulatory entities only report the adoption status of one EHR application, "Ambulatory EHR." Therefore, it is a binary indicator of whether this application is "Live and Operational" or "To Be Replaced" for an ambulatory entity in a given year.

Hospital Inpatient Cost

CMS Medicare Cost Reports (MCR) are publicly available data files that contain reliable financial information for approximately 6,000 hospitals across the US. It reports seven cost categories such as *General Services* (pharmacy, central sterile services, medical consumables); *Ancillary Services* (operating rooms, labor and delivery room, anesthesiology, labs, radiology, and other medical services); *Inpatient Routine Services* (nursery, special wards, and intensive care unit costs); *Outpatient Services* (clinics or emergency centers related costs); *Non-reimbursable*

[1] "To Be Replaced" indicates an application is still in use but will be replaced with an application that has been contracted (HIMSS Database Documentation)

(gift, flower, coffee shop, and research); *Other reimbursable* (home program dialysis and other durable equipment); *Special Purpose* (organ acquisition and ambulatory surgical center).

Table 2: Descriptive Statistics

Variable	Definition	Mean	Std. Dev.
Inpatient Cost Per Discharge	Sum of General, Inpatient and Ancillary Costs /No. of Discharges	$25,241.66	$60,541.95
Focal Hospital EHR	Ratio of adopted EHR applications to the total EHR applications. Ranges between 0 and 1 for a hospital	0.66	0.34
Ambulatory EHR	Average ambulatory EHR application adoption for all the entities in an HRR. Binary 0/1 indicator for each entity.	0.57	0.31
Focal Hospital HIE	Binary indicator if the hospital is participating in an information exchange initiative	0.44	0.50
Ambulatory HIE	Average ambulatory HIE application adoption for all the entities in an HRR. Binary 0/1 indicator for each entity.	0.40	0.25
Urban	Binary indicator if majority of zip codes in an HRR are Urban	0.66	0.47
Population Density	Total population of the HRR divided by the land area of the HRR	906.38	3179.26
Clinic Density	No of ambulatory entities in an HRR	167.75	157.61
Distance (in miles)	Median pairwise distance from focal hospital to ambulatory entities, averaged for an HRR	40.45	40.97
Hospital-level controls			
Discharges	No. of discharges	6105.1	6388.52
Inpatient Days	Inpatient days	29992.45	30436.11
No of Beds	Number of beds	136.45	115.31
FTE	Total interns, residents, paid and non-paid full-time employees	735.41	714.07
CMI	CMI or case mix index represents the average diagnosis-related group (DRG) relative weight for a hospital	1.39	0.27
HRR-level controls			
% 65 and older	Average percentage population that is 65 and older	13.51%	3%
% Graduate	Average % population that are college graduate	25.29%	6.7%
Income	Median household income	47773.84	10564.73
Tot Population	Total population	414,072.00	360,020.90

Since the reporting period (i.e., fiscal year) varies for each provider in the MCR database, we normalized the extracted data for 365 days to obtain an annual aggregate for each cost category. Hospitals with more than two years of missing data for inpatient cost categories were dropped.

The remaining missing cost data for all inpatient cost categories are imputed using linear interpolation, followed by dropping outlier hospitals that fall within top and bottom 5% of inpatient costs. Further, we deflated the cost values to adjust price inflation using World Bank data with 2015 as the base year. The main dependent variable is inpatient cost per discharge, calculated as the total of the three main inpatient related cost categories (General Services, Ancillary, and Inpatient Routine) divided by the number of discharges. This measure captures the cost centers directly related to clinical operations in the inpatient settings.

Control Variables

We control for several hospital-level and region-level characteristics that may affect hospital costs. Hospital-level controls include beds, inpatient days, full-time employees (FTEs), and case mix index (CMI). No. of beds is defined as beds available for use at the end of the cost reporting period and does not represent no. of licensed or staffed beds. Inpatient days of a hospital represent the length of stay for all hospitalizations in a reporting period. FTE is the sum of interns, residents, and the average paid and unpaid employees in a reporting period. Finally, CMI is the average diagnosis-related group (DRG) relative weight representing the complexity of inpatients for a hospital. It is calculated by summing the DRG weights for all Medicare discharges and dividing by the number of discharges. We also capture HRR-level regional control variables, including the percentage of population 65 and older, percentage of the population with a college degree, median household income, and the total population.

Summary Statistics

Our balanced panel has an average of 11.55 hospitals and 168 ambulatory clinics in each HRR, with a median distance of 33.78 miles from a focal hospital to ambulatory facilities in its HRR. Descriptive statistics for our dependent, independent, and control variables are presented in Table 2. The mean hospital EHR adoption is 0.66, which means that a little more than three EHR applications out of five (CDR, CDSS, CPOE, OE, PD) are adopted. The mean ambulatory EHR is 0.57, which means that more than half of ambulatory facilities in each HRR have adopted the ambulatory EHR application. These statistics are consistent with previous findings, validating our variable construction (Henry et al. 2016; Rudin et al. 2019).

Baseline Model and Estimation Results

We test our hypothesis by examining how the focal hospital's inpatient cost per discharge is affected by the EHR adoption of surrounding ambulatory entities in the same HRR. Specifically, we estimate the following fixed effects model:

$$log(IpCost/Discharge)_{i,t} = \beta_0 + \beta_1\, Hospital\, EHR_{i,t} + \beta_2\, Ambulatory\, EHR_{h,t} + \theta\, X_{i,t} + \delta\, Z_{ht} + \alpha_i + \lambda_t + e_{i,t} \qquad (1)$$

where the dependent variable $log(IpCost/Discharge)_{i,t}$ is the inpatient cost per discharge of the focal hospital *i* at year *t*. We take the logarithm transformation to account for the skewed distribution of the cost. We capture the EHR adoption of focal hospital using $Hospital\, EHR_{i,t}$. We measure the spillover effect of EHR adoption of ambulatory entities with $Ambulatory\, EHR_{h,t}$, which is the average EHR adoption of all ambulatory entities in HRR *h* at year *t*. $X_{i,t}$ includes hospital-specific characteristics as we have discussed earlier and $Z_{h,t}$ represents the HRR-level controls. Since these regional control variables are available only for 2010, we multiply these factors by the time trend (Atasoy et al. 2018; Dranove et al. 2014). α_i is the hospital fixed effects that control for time-invariant hospital heterogeneity and λ_t is the year fixed effects that control for economic shocks. We cluster standard errors by the hospital to account for potential serial correlation.

Therefore, parameter estimates β_1 measure the effect of EHR adoption of the focal hospital on its own inpatient cost per discharge while β_2 measures the spillover effect of EHR adoption of geographically proximal ambulatory entities on the inpatient cost per discharge of the focal hospital. To mitigate reverse causality concerns, we extend our baseline model specification to include the lagged effects of Hospital EHR and Ambulatory EHR at years t-1, t-2, and t-3.

Table 3: Ambulatory EHR Spillover Effects

	DV: log(Inpatient Cost/Discharge)			
VARIABLES	(1)	(2)	(3)	(4)
Focal Hospital EHR	0.047***	0.032***	0.034***	0.035***
	(0.010)	(0.009)	(0.010)	(0.011)
Focal Hospital EHR(t-1)		0.025***	0.009	0.009
		(0.007)	(0.007)	(0.008)
Focal Hospital EHR (t-2)			0.026***	0.004
			(0.009)	(0.007)
Focal Hospital EHR (t-3)				0.028***
				(0.009)
Ambulatory EHR	-0.031***	-0.007	-0.005	-0.004
	(0.010)	(0.009)	(0.010)	(0.010)
Ambulatory EHR(t-1)		-0.028***	-0.003	-0.001
		(0.009)	(0.009)	(0.009)
Ambulatory EHR(t-2)			-0.037***	-0.017**
			(0.008)	(0.008)
Ambulatory EHR(t-3)				-0.034***
				(0.008)
Observations	33,397	30,828	28,259	25,690
R-squared	0.591	0.573	0.550	0.530
No. of Hospitals	2,569	2,569	2,569	2,569
Hospital FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Notes: Hospital-level controls for the focal hospital and for the other hospitals in the HRR: log(Inpatient Days), log(Bed No.), log(Total FTE), Case Mix Index. HRR-level controls: Percent residents 65 years and older, Percent college graduate, log(Total population), log(Median household income). Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

Estimation Results of Baseline Model

Table 3 shows the estimation results of equation (1). We observe that the focal hospital EHR adoption is significant with a coefficient of 0.047, indicating that the adoption of each additional EHR application in the focal hospital (i.e., 0.2 increase in *Hospital EHR*) increases its own inpatient cost by 0.94% (0.2*0.047) in the same year. This finding is consistent with extant literature (Dranove et al. 2014) and implies that EHR adoption does not provide economic gains directly. Furthermore, we observe negative coefficient of Ambulatory EHR (coefficient = -0.031, p-value < 0.01), indicating the significant spillover effect of ambulatory EHR adoption in reducing the inpatient cost at the focal hospital. Specifically, for an average HRR with 169 ambulatory clinics, if an additional clinic adopts EHR, the focal hospital's inpatient cost reduces by 0.018% (1/169*0.031), which corresponds to $27,000 cost savings per hospital per year.

We also test the lagged effect and present the results in columns (2) – (4). We observe that the spillover effect of EHR adoption at ambulatory clinics emerges in the current year and persists for over four years. To be more specific, when an additional clinic adopts EHR for an average HRR, the focal hospital decreases its inpatient cost per discharge by 0.056% cumulatively in four years, equivalent to $51,000 cost reductions. Overall, the results provide empirical evidence to support our hypothesis that the EHR adoption at ambulatory clinics has a spillover effect on reducing inpatient hospital costs.

Ambulatory EHR Spillover Mechanisms

In this section, we examine the mechanism through which the benefits from ambulatory EHR adoption can spillover to neighboring hospitals in a regional healthcare market.

Ambulatory EHR Spillover Effects on Different Cost Categories

In theory, the EHR spillover effect is grounded in the exchange of patient medical information, such as lab results, radiology images, and summary of care, which impacts *costs related to direct patient care* but not on non-clinical operations within a hospital. Therefore, we analyze the spillover effect of ambulatory EHR adoption on different cost categories to support this mechanism. We anticipate a significant spillover effect on inpatient cost categories but insignificant on non-reimbursable costs (includes gift and coffee shop costs), other reimbursable costs (ambulance, home health, medical equipment rental), and special-purpose costs (organ acquisition costs).

We present the results in Table 4, where we observe the significant spillover effect of ambulatory EHR adoption on major inpatient cost categories such as general and ancillary services. Contrary to the expectation, the effect on inpatient routine cost is insignificant. This could be because it includes costs related to intensive care units that operate with internal hospital transfers and information exchange and therefore may not concern with patient or information exchange from ambulatory clinics outside of the hospital. Further, the coefficient of ambulatory EHR is insignificant for non-inpatient cost, which lends support to health information sharing as the underlying mechanism of the EHR spillover effect.

Table 4: Ambulatory EHR Spillover Effects by Cost Categories

	DV: log(Cost Category/Discharge)						
	Inpatient Cost Categories			Non-Inpatient Cost Categories			
	General	Inpatient Routine	Ancillary	Outpatient	Non-re-imbursable	Other- re-imbursable	Special Purpose
Focal EHR	0.037***	0.011	0.001	0.073***	0.056	0.062	-0.118**
	(0.009)	(0.011)	(0.010)	(0.021)	(0.079)	(0.077)	(0.054)
Focal Hospital EHR(t-1)	0.022***	0.017**	0.023***	0.043**	0.063	0.187***	0.038
	(0.008)	(0.008)	(0.008)	(0.018)	(0.076)	(0.061)	(0.046)
Ambulatory EHR	-0.023*	-0.007	0.002	-0.017	0.118	-0.007	0.186**
	(0.014)	(0.011)	(0.010)	(0.022)	(0.096)	(0.092)	(0.079)
Ambulatory EHR(t-1)	-0.020**	-0.002	-0.024***	-0.032	-0.012	-0.137*	-0.001
	(0.010)	(0.009)	(0.009)	(0.019)	(0.083)	(0.073)	(0.059)
N	30,828	30,828	30,828	30,528	29,616	16,860	24,624
R-sq	0.229	0.304	0.299	0.232	0.113	0.055	0.050
Hospitals	2,569	2,569	2,569	2,544	2,468	1,405	2,052
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Notes: Hospital-level controls for the focal hospital and for the other hospitals in the HRR: log(Inpatient Days), log(Bed No.), log(Total FTE), Case Mix Index. HRR-level controls: Percent residents 65 years and older, Percent college graduate, log (Total population), log(Median household income). Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1							

Ambulatory EHR Spillover Effects due to Geographic Agglomerations

Healthcare providers exchange patient records because they share the same pool of patients. If there is no patient sharing between hospitals and ambulatory entities, they should not exchange patient information due to Health Insurance Portability and Accountability Act (HIPPA) regulations. Following this line of logic, the underlying driver for the regional spillover effect (i.e., patient information sharing) is stronger when there are more shared patients. Therefore, we speculate that regional healthcare market characteristics, such as urban-rural, population density, the distance between the focal hospital and neighboring ambulatory entities, and the number of ambulatory entities in each HRR can influence the volume of patients and access to different types of healthcare services available thus forming geographic agglomerations. Results are presented in Table 5.

Table 5: Ambulatory EHR Spillover Effects by Geographical Agglomerations

	DV: log(Inpatient Cost/Discharge)			
	(1)	(2)	(3)	(4)
Focal Hospital EHR	0.045***	0.042***	0.046***	0.042***
	(0.010)	(0.010)	(0.010)	(0.010)
Ambulatory EHR	-0.026**	-0.026**	-0.019*	-0.036***
	(0.011)	(0.011)	(0.011)	(0.011)
Ambulatory EHR x Urban	-0.080***			
	(0.015)			
Ambulatory EHR x Pop Density		-0.037***		
		(0.005)		
Ambulatory EHR x Distance			0.038***	
			(0.009)	
Ambulatory EHR x Clinic Density				-0.045***
				(0.005)
N	33,397	33,397	33,397	33,397
R-sq	0.593	0.594	0.592	0.595
Hospitals	2,569	2,569	2,569	2,569
Hospital FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: Hospital-level controls for the focal hospital and for the other hospitals in the HRR: log(Inpatient Days), log (Bed No.), log (Total FTE), Case Mix Index. HRR-level controls: Percent residents 65 years and older, Percent college graduate, log(Total population), log(Median household income). Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

First, *urban* areas have higher population density and access to a variety of basic and advanced healthcare services and are thus expected to have stronger spillover effects in reducing the cost of care. We interact the Ambulatory EHR variable with an *Urban* HRR dummy that takes a value of 1 if more than 80% of the zip codes in an HRR are classified as urban, based on RUCA classification[2]. The coefficient of interaction term Ambulatory EHR and Urban dummy indicates Ambulatory EHR spillover effects when HRR is urban. Table 5, column 1 exhibits that this interaction is significant, implying significant effects within urban regional markets. Conversely, the baseline spillover effect of Ambulatory EHR represents the effects in a rural area. Regional adoption of Ambulatory EHR can reduce inpatient costs of rural hospitals by 0.026% and urban hospitals by 0.106%.

Second, similar to the previous rationale, HRRs with higher *population density,* calculated as population per square mile, would mean a higher number of referral cases and thus higher spillover effects. Again, as expected, we find significant effects; for a unit increase in population density from its mean, regional ambulatory EHR adoption will reduce inpatient costs by 0.063% (Table 5, col 2).

Third, we examine the effects of *geographical distance* of ambulatory entities to the focal hospital in an HRR. Distance is calculated as the median pairwise distance from hospital to ambulatory entities, aggregated for each HRR. As expected, results indicate that inpatient cost per discharge increases as the pairwise distance in a region increase. In particular, results (Table 5, col 3) indicate that with a unit increase in distance between focal hospitals and neighboring ambulatory entities, regional ambulatory EHR adoption will increase inpatient cost by 0.019%. This further confirms the importance of geographical distance in realizing spillover effects of EHR adoption.

[2] https://www.ers.usda.gov/data-products/rural-urban-commuting-area-codes/

Finally, spillover effects are expected to be stronger in HRR with higher *clinic density*, measured as the total no. of ambulatory entities in an HRR divided by the total land area of HRR. More ambulatory entities per square mile mean higher likelihood of referral cases to hospitals. We find that as more ambulatory entities are added to an HRR, the ambulatory EHR spillover effects reduce the focal hospital inpatient cost by 0.067% (Table 5, col 4).

Overall, ambulatory EHR spillover effects have greater benefits for hospitals located in urban areas, densely populated areas, or areas with a higher number of ambulatory services. These findings underscore the importance of information exchange among regional healthcare agglomerations, through which spillover effect materializes.

Ambulatory EHR Spillover Effects in Integrated Delivery Systems

It is generally easier to share patient data if providers are in the same parent organization due to fewer concerns about competition and privacy and better system interoperability. Therefore, we expect the exact mechanism to pronounce the cost savings if hospitals and ambulatory entities are a part of the same parent integrated delivery system (IDS). However, considering the larger referral market size of HRR and the fact that people usually travel within 10 miles for their routine healthcare needs (Yen 2013), we expect this mechanism to materialize in a smaller geographical area where routine referral activity is expected. To test this, we first measured average ambulatory EHR adoption for each IDS within an HRR (labeled as Ambulatory EHR In IDS) and average ambulatory EHR adoption for each IDS within the same HRR except for the focal IDS (labeled as Ambulatory EHR Out IDS). Next, we calculate the median of the pairwise distances between the focal hospital and all other ambulatory entities in an HRR and expect effects to be significant if this median distance is <=10 miles.

Table 6: Ambulatory EHR Spillover Effects In and Out IDS

	DV: log(Inpatient Cost/Discharge)		
VARIABLES	(1)	(2)	(3)
Focal Hospital EHR	0.043***	0.042***	0.040***
	(0.010)	(0.011)	(0.012)
Ambulatory EHR In IDS X Mile10	0.025**	0.030**	0.025*
	(0.012)	(0.012)	(0.013)
Ambulatory EHR Out IDS X Mile10	0.024	0.029*	0.027
	(0.015)	(0.017)	(0.018)
Mile10	-0.001	0.002	0.005
	(0.014)	(0.018)	(0.018)
Ambulatory EHR In IDS	-0.025**	-0.026**	-0.020*
	(0.011)	(0.011)	(0.012)
Ambulatory EHR In IDS (t-1) X Mile10		-0.006	-0.006
		(0.005)	(0.004)
Ambulatory EHR In IDS (t-2) X Mile10			-0.004
			(0.005)
Ambulatory EHR Out IDS	-0.036**	-0.030*	-0.029*
	(0.016)	(0.017)	(0.017)
Ambulatory EHR Out IDS (t-1) X Mile10		-0.010	0.006
		(0.009)	(0.009)
Ambulatory EHR Out IDS (t-2) X Mile10			-0.021**
			(0.009)
Observations	28,575	25,920	23,353
R-squared	0.551	0.525	0.493
Number of Hospitals	2,482	2,462	2,442
Hospital FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Notes: Hospital-level controls for the focal hospital and for the other hospitals in the HRR: log(Inpatient Days), log(Bed No.), log(Total FTE), Case Mix Index. HRR-level controls: Percent residents 65 years and older, Percent college graduate, log(Total population), log(Median household income). Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1			

Next, we created a dummy variable, *Mile10*, which takes a value of 1 if the median distance is >10 miles. We then interact it with ambulatory EHR in and out IDS variables to examine the difference in spillover effects when ambulatory entities that belong to the same IDS as focal hospital are located closer than when they are located farther. Results from Table 6, col 1, show that for ambulatory entities located within 10 miles of the focal hospital, spillover effects are significant if ambulatory entities are also affiliated with the focal hospital's parent organization. However, this effect is pronounced if ambulatory entities are not affiliated with the focal hospital's parent organization. Further, we observe significant lagged effects when ambulatory entities and the focal hospital are not affiliated with the same parent organization and located farther than 10 miles. These findings have two important implications. First, regardless of the IDS affiliation, inpatient cost reduces when hospitals exchange health information with ambulatory entities within their 10-mile distance. Second, regardless of the distance, health information exchange with outside IDS ambulatory entities reduces the focal hospital's inpatient cost (Table 6 col 3), supporting our central idea to move from 'competitive advantage' to a 'sustained cooperation' mindset.

Ambulatory EHR Spillover Effects in Health Information Exchanges

Another aspect that plays an integral role in realizing network externalities of EHR systems is if providers exchanging patient information are participating in and using health information exchange (HIE) applications. HIE applications are an interorganizational information system that facilitates the exchange of medical information among disparate providers (Adjerid et al. 2018). By 2018, almost 96% of hospitals and 85% of physician offices have successfully adopted EHR systems, yet information exchange among providers is still lagging at 41% (Bates and Samal 2018). Despite the low adoption and actual use of HIE applications, it is the single-most direct measure of information exchange among providers. Since the HIMSS database reports ambulatory HIE application adoption data only for 2016 and 2017, our analyses are limited to the information based on two years.

To this end, we examine this mechanism hierarchically. First, we find significant (Table 7 col 1; Focal Hospital HIE participation data from 2006-2017 included) or marginally insignificant (Table 7 col 2, 3; Focal Hospital HIE participation data from 2016-2017 included) cost reduction when hospitals adopt HIE applications. These results are consistent with Adjerid et al. (2018 and Walker (2018. Although not a focus of this study, this is an interesting finding that highlights the economic value of HIE adoption by the focal hospital. Most importantly, we find significant spillover effects from neighboring ambulatory entities' HIE adoption (Table 7 col 2). The effects are stronger when the HIE application is adopted by ambulatory entities that are not affiliated to the focal hospital's parent organization (Table 7 col 3). Again, these results support the paper's central idea that healthcare providers may move from a 'competitive advantage' to a 'sustained cooperation' mindset. Interestingly, we find marginally insignificant spillover effects from HIE applications adopted by ambulatory entities that share an affiliation with focal hospital IDS. A possible explanation could be a mechanism related to the type of HIE applications used within hospital systems that can be examined using more granular data in the future.

Table 7: Ambulatory HIE Spillover Effects

	DV: log(Inpatient Cost/Discharge)		
VARIABLES	(1)	(2)	(3)
Focal Hospital EHR	0.050***	0.111**	0.110
	(0.010)	(0.056)	(0.069)
Focal Hospital HIE	-0.014***	-0.008	-0.007
	(0.005)	(0.015)	(0.017)
Ambulatory HIE		-0.023*	
		(0.014)	
Ambulatory HIE In IDS			-0.009
			(0.007)
Ambulatory HIE Out IDS			-0.032**
			(0.014)
Observations	32,721	5,138	4,721
R-squared	0.604	0.236	0.205
Number of Hospitals	2,517	2,569	2,388
Hospital FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Notes: Hospital-level controls for the focal hospital and for the other hospitals in the HRR: log(Inpatient Days), log(Bed No.), log(Total FTE), Case Mix Index. HRR-level controls: Percent residents 65 years and older, Percent college graduate, log(Total population), log(Median household income). Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1			

Table 8: Lead Ambulatory EHR Adoption

	DV: log(Inpatient Cost/Discharge)		
VARIABLES	(1)	(2)	(3)
Focal Hospital EHR	0.048***	0.050***	0.046***
	(0.010)	(0.009)	(0.009)
Ambulatory EHR (t+3)			-0.008
			(0.011)
Ambulatory EHR (t+2)		-0.011	-0.009
		(0.010)	(0.009)
Ambulatory EHR (t+1)	-0.012	-0.005	-0.008
	(0.010)	(0.008)	(0.008)
Ambulatory EHR	-0.000	-0.002	0.000
	(0.008)	(0.008)	(0.008)
Ambulatory EHR(t-1)	-0.027***	-0.025***	-0.026***
	(0.009)	(0.008)	(0.008)
Observations	28,259	25,690	23,121
R-squared	0.573	0.574	0.542
No. of Hospitals	2,569	2,569	2,569
Hospital FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: Hospital-level controls for the focal hospital and for the other hospitals in the HRR: log(Inpatient Days), log(Bed No.), log(Total FTE), Case Mix Index. HRR-level controls: Percent residents 65 years and older, Percent college graduate, log(Total population), log(Median household income). Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Robustness Checks

We find support for our hypothesis controlling for individual and time-fixed effects and related mechanisms. Nevertheless, ambulatory EHR adoption may still be prone to potential endogeneity issues like reverse causality and spurious correlation arising from other confounding factors discussed and addressed in this section.

First, reverse causality could occur if the reduction in focal hospitals' inpatient cost led to increased ambulatory EHR adoption in an HRR. For example, if a hospital in a geographic area enjoys greater margins due to a reduction in costs and thus expands its business by adding new services, it can attract more new patients. This can trigger the neighboring ambulatory care entities to adopt EHR systems to keep up with the increased healthcare needs of the market. To address this issue, we utilize the ambulatory EHR lead (t+1, t+2, t+3) and lag (t-1) variables to show no significant relationship between focal hospital cost and future ambulatory EHR adoption. These results are presented in Table 8, columns 1,2, and 3, implying reverse causality is not an issue.

Another problem could be the effect of other time-varying confounding variables leading to a spurious correlation. We present two falsification tests to address this problem. First, consistent with the extant spillover literature, the effects should not be insignificant in the absence of geographic agglomerations. This means that a focal hospital cost should be unaffected by EHR adoption of ambulatory entities that do not fall within its HRR or are located far away from the focal hospital location. If this is true, then the model supports the referral network model discussed earlier. To this end, we shuffled focal hospital HRR to match it with the ambulatory EHR value from a different HRR and found that effects are not significant, which supports our model (Table 9). Second, Table 4 results, with insignificant ambulatory EHR spillover effects on non-inpatient cost categories, also support falsification.

Table 9: Shuffled Ambulatory EHR Spillover Effects

	DV: log(Inpatient Cost/Discharge)			
VARIABLES	(1)	(2)	(3)	(4)
Focal Hospital EHR	0.046***	0.046***	0.045***	0.040***
	(0.010)	(0.010)	(0.012)	(0.012)
Ambulatory EHR shuffled	0.002	0.001	-0.004	-0.003
	(0.008)	(0.008)	(0.008)	(0.009)
Ambulatory EHR shuffled (t-1)		0.004	0.002	0.000
		(0.007)	(0.006)	(0.006)
Ambulatory EHR shuffled (t-2)			0.008	0.006
			(0.007)	(0.006)
Ambulatory EHR shuffled (t-3)				0.006
				(0.008)
Observations	33,397	30,828	28,259	25,690
R-squared	0.591	0.572	0.548	0.528
No. of Hospitals	2,569	2,569	2,569	2,569
Hospital FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Notes: Hospital-level controls for the focal hospital and for the other hospitals in the HRR: log(Inpatient Days), log (Bed No.), log (Total FTE), Case Mix Index. HRR-level controls: Percent residents 65 years and older, Percent college graduate, log(Total population), log(Median household income). Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

Discussion

Research has shown that health information exchange reduces readmissions, duplicate tests, medical errors and improves patient outcomes. However, healthcare administrators have expressed concern over the sustainability of the HIE business model (Adler-Milstein et al. 2016; Everson and Adler-Milstein 2020). To this end, empirical evidence on the economic value of information exchange between disparate providers can foster patient-related health information exchange, thereby propagating a cooperative business environment. This is particularly important when the federal government promotes interoperability through stage 3 meaningful use while healthcare providers are reluctant to share valuable patient information and engage in information blocking practices (Everson et al. 2021). Healthcare providers are central actors to the care delivery continuum, and thus forcing a policy that disrupts their business model may ensue unintended consequences. We derive from theoretical foundations that seek evidence supporting cooperation among users of interorganizational systems within reciprocal networks (Kumar and Van Dissel 1996; Volkoff et al. 1999). Conflict may arise if there is a limited benefit for participants for referral networks. To this end, since there are limited direct benefits (Dranove et al. 2014), we examine indirect cost benefits based on referral activity between hospitals and ambulatory entities and provide empirical evidence on the business value of information exchange.

Despite the convincing results, this work has several limitations. First, as with all studies based on archival data, this work relies on the HIMSS database, where the classification of ambulatory entities is not granular and includes primary care clinics, specialty outpatient clinics, urgent care, diagnostic centers, and various therapy and rehabilitation centers. Our research model can be improved if this classification separates major ambulatory categories. A more granular level classification of ambulatory entities could facilitate the examination of interface c and e (Figure 1 Panel B) separately, providing a more detailed understanding of the spillover effects in the referral network model. Second, ambulatory HIE application adoption data is only available for two years in the HIMSS database and thus our HIE spillover effects mechanism results are restricted to two years. In addition, more granular data on types of HIE applications could provide a better understanding of HIE mechanisms discussed in section 6.4. We have also limited the scope of this study to examine the spillover effects for one direction in the referral network model interface c and e (Figure 1 Panel B). Nevertheless, this research provides significant contributions to both research and practice.

Theoretical Implications

This study makes several important contributions to the literature. First, our proposed healthcare referral network provides a conceptual framework for future researchers to study HIT network externalities. E.g., every new technology adopted in healthcare like EHR mobile apps, home monitoring devices, or IoT can be examined for spillover effects grounded in the referral network model. Network effects provide essential empirical evidence that helps in the adoption, use, and diffusion of new technologies over time. Second, we empirically tested interfaces c and e (Figure 1 panel B) of our referral network model to show significant ambulatory EHR adoption spillover effects on focal hospital's inpatient cost. We further validated this effect by exploring several mechanisms that can pronounce this effect. To this end, we found that hospitals mainly save in the case of pharmacy and medical consumable-related cost centers. In addition, hospitals can save more if they are located in urban, densely populated areas with more ambulatory entities located closer to the focal hospital. Third, to the best of our knowledge, network externalities and information exchange mechanisms between ambulatory care entities and hospitals are largely unexplored. Fourth, our healthcare context results conform to the upstream/downstream spillover mechanisms, as noted by the work of Cheng and Nault (2012). Thus, our model extends the EHR spillover literature using data from recent years.

Most importantly, our empirical model based on complex interorganizational relations (IOR) and results supporting sustainable cooperation using IOS calls IS researchers to revive the discussion on information infrastructure (II) and the success of IOS based on complex interorganizational relations (IOR) among healthcare providers (Aanestad and Jensen 2011; Williams 1997).

Practical Implications

With the federal focus on promoting interoperability while prohibiting information blocking practices, it is more critical than ever to examine the business value of information exchange to ease providers' skepticism around exchanging information with unaffiliated providers. Our results suggest that hospitals can significantly save inpatient costs even when they share patient information with unaffiliated neighboring ambulatory entities. This is an important finding that supports cooperation among disparate providers, much needed for building the business care for information exchange, interoperability, and value-based care delivery models. Consequently, it may help the healthcare business environment to move from a competitive advantage (holding on to the patient information) to a sustained cooperation mindset (sharing patient information). Once the culture of sustained cooperation is propagated, the demand for information-sharing capabilities of healthcare applications will increase. This shift in market demand may drive EHR vendors to evolve the current generation of EHR systems for their interoperability capabilities. Finally, quantifying the economic impact is crucial for policymakers, healthcare providers, and EHR vendors to understand the high-level cost-benefit of EHR.

Conclusion

Digital transformation is touted as the next most significant reform in healthcare, but the current public health landscape has made it a global priority. Further, the recent pandemic has shown how network externalities play a significant role in healthcare. Whether it is spreading the virus, containing it, achieving herd immunity, or providers and health systems coming together to fight the pandemic. In this light, fostering cooperation among disparate healthcare providers is more critical than ever. This work supports the idea of sustained cooperation among providers facilitated through the adoption and use of interorganizational systems.

Information exchange lies at the heart of the digital transformation, and therefore it is imperative to understand all the possible interfaces of care delivery and the associated network externalities to develop a complete understanding of its indirect business value. This work and Atasoy et al. (2018 provides empirical evidence on the business value of a cooperative healthcare business environment. We also present a holistic healthcare referral network model of patient and information exchange to examine spillover effects of new technology adoption in healthcare. Overall, this work adds to the existing knowledge on network externalities in healthcare.

CHAPTER III

ESSAY 2: TECHNOSTRESS AMONG PHYSICIANS: CONCEPTUALIZING STRESSFUL EHR DESIGN FEATURES

Introduction

Growing evidence indicates that EHR use is causing physicians and nurses to work for longer hours and thus experience job-related stress. Mandatory use of inefficient EHR systems has forced physicians to work outside of their regular working hours (Adler-Milstein et al. 2020). A news article (Spector 2018) reported an excerpt from a doctor's interview who had quit medicine after 20 years of practice:

> *"I began to feel like an easily replaceable cog in the health care machine. With the [enforcement] of EHRs, I had to spend more time as a scribe. One night a child I was treating had a seizure and I couldn't get the medicine to enable them to breathe because their chart wasn't in the system yet. This kid was fixing to die and I, the doctor, couldn't get the medicine. It was demoralizing".*

In addition, associated costs based on physician turnover and reduced clinical hours can amount to $4.6 billion annually (Han et al. 2019). A survey (PhysicianFoundation 2018) found that electronic health records or EHR design is one the least satisfying aspect of medical practice and that 29% of physicians plan to quit medicine. This could have serious ramifications, in the face of the existing physician shortage which is projected to reach 120,000 by 2030 (Heiser 2019). The unintended consequences stemming from the use of IT is significant among physicians and may offset the benefits of the HIT reform (Tarafdar et al. 2007).

The phenomenon of technostress among individuals is the euphemism for the dark side of IT use and has been the focus of researchers and practitioners as it has been shown to significantly impact employee wellbeing, job satisfaction, intention to leave, and attrition (Califf et al. 2020; Ragu-Nathan et al. 2008a; Tarafdar et al. 2010). This rich stream of literature is evolving and recent works have highlighted the need to investigate EHR design features that enhance eustress and mitigate distress. It is noted that extant technostress literature has no information on stress-inducing design features and the associated remedial implications (Califf et al. 2020; Tarafdar et al. 2019). With a pragmatic epistemological perspective, we utilize qualitative research methods to study this unexplored aspect of technostress within the healthcare context (Yin 2015). Our main research question is, "What specific EHR characteristics cause stress among physicians?".

Notably, this is the first research that explores IS design concepts within a contextual technostress environment, and by doing so, we inform theory and practice on EHR design themes that mitigate the unintended consequences of EHR use. In addition, our work contributes to adding depth to the extant literature on physician burnout and technostress, as discussed in the next section.

Literature Review and Theoretical Foundation

Past literature has shown that physicians are generally not satisfied with the EHR systems and thus prone to professional burnout (Shanafelt et al. 2016). It is also found that time spent on the EHR at home, daily frustration with the EHR, and time for documentation are all significantly associated with burnout among healthcare professionals (Harris et al. 2018). In addition, a study (Gardner et al. 2019) found a significant relationship between HIT-related stress and physician burnout. Further, a qualitative assessment of a focus group of 41 primary care physicians and finds excessive data entry, inefficient user interface, insufficient information exchange capabilities, information overload, interference with patient-physician relationship, and ergonomic issues as the unintended consequences of HIT use (Kroth et al. 2018). While this stream of literature describes the problem and related themes, it lacks in identifying specific EHR design features that lead to technostress among physicians.

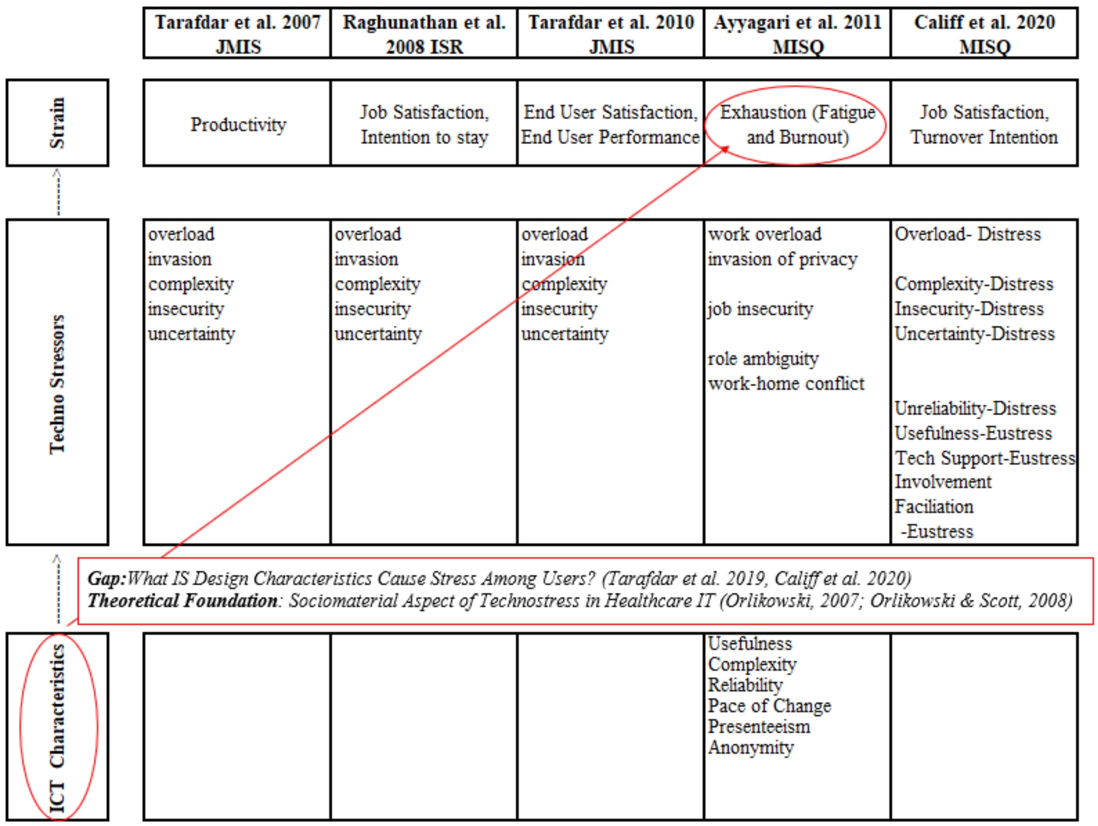


Figure 2: Overview of Key Literature on Technostress

In a similar vein, past literature on technostress has successfully theorized the mechanisms that impact job satisfaction among individuals (Ayyagari et al. 2011; Califf et al. 2020; Ragu-Nathan et al. 2008b; Tarafdar et al. 2010). Technostress is defined as "one of the fallouts of an individual's attempts and struggles to deal with constantly evolving ICTs and the changing cognitive and social requirements related to their use". This phenomenon is best explained using the theoretical foundation of the transaction-based model of stress which examines the causal direction between stressors and individual response to them (Ragu-Nathan et al. 2008a). Stressors or stimulating conditions are defined as events, demands, stimuli, or conditions encountered by individuals in the work/organizational environment as factors that create stress. Commonly studied stressors that impact job satisfaction are usefulness, tech-support, involvement facilitation, work-overload, complexity, uncertainty, insecurity, and invasion.

Usefulness is when users perceive HIT to be useful in enhancing their job performance. It is the foundational idea of HIT reform, and it has been shown that HIT adoption has led to better clinical outcomes (Bardhan et al. 2015; Pinsonneault et al. 2017). *Work-overload* is defined as situations that demand HIT users to work longer and faster. With the increased adoption of EHR and its meaningful use requirements, the workload has increased to the extent that both physicians and nurses have to use their time outside of their regular work hours (Adler-Milstein et al. 2020; Califf et al. 2020). *Complexity* loosely represents the inherent difficulties in the HIT environment that may arise from long and constant learning curves, cumbersome HIT policies, and hassles in using HIT to get a routine job done (Tarafdar et al. 2019). *Uncertainty* arises when the HIT environment frequently changes such that it causes workflow inefficiencies and the associated frustrations.

These stressors, arising out of IT use, can be appraised as positive (challenge) or negative (hindrance). Challenge techno-stressors can lead to *techno-eustress* and motivate individuals to cope with the associated stress and increase satisfaction. In contrast, hindrance techno-stressors can lead to *techno-distress* and reduce satisfaction. It is also theorized that this duality can be reconciled to address the inadequacies in IT design such that it enhances techno-eustress and mitigates techno-distress (Califf et al. 2020; Tarafdar et al. 2019).

Figure 2. presents a summary of key work in technostress literature and highlights the positioning of this study within the socio-technical aspect of technostress. Based on this, only Ayyagari et al. (2011) has attempted to explore the antecedents of techno-stressors. Nevertheless,

their conceptualization of differences between ICT characteristics and techno stressors is somewhat blurred. Thus, this work attempts at understanding specific IS design characteristics that directly impact the stress manifestation (strain) among physician users, leaving out the psycho-social part of this framework which may want to establish a relationship between ICT characteristics and stressors.

Furthermore, there is a recent call to conceptually understand IS design features that are manifested as techno stressors (Califf et al. 2020; Tarafdar et al. 2019). These IS design features could be indicative of a simplified design interface, application functionality, and performance, information prioritization features, information on privacy and security aspects of data collection, etc., (Tarafdar et al. 2019). This work addresses this call and examines specific EHR-driven characteristics that are manifested as stress among physicians.

Research Design

This IRB-approved study uses semi-structured interviews to conceptualize specific EHR characteristics that cause stress among physicians. Interviews were conducted at an academic health center and then additional participants were recruited using snowballing technique resulting in a pool of physicians representing all care delivery levels i.e., primary care physicians (family medicine, internal medicine, pediatrics); hospitalists (internal medicine, family medicine, infectious diseases); and specialists (emergency medicine, general surgery, obstetrics and gynecology, hepato-transplant, hemato-oncology, osteopathic manipulation, pulmonary medicine, psychiatry). We interviewed 24 physicians out of which 17 either feel stressed or burned out due to the use of EHR. There are 14 Female and 10 male physicians in our sample with an average age of 41 years. On average, participants rate their comfort level with technology to be 8 on a scale of 10 and an average of 11 years of experience working with EHR systems. We argue that younger participants with greater technological experience and comfort are better suited to provide quality insights and explanations on stressful EHR design features. Thus, we can say that our sample characteristics are balanced in terms of gender and specialties, and representative of our population of interest.

The interview protocol was designed to gain a deeper understanding of the technostress phenomenon among physicians using an explicit open-ended question that what specific EHR characteristics cause stress? In the case of generic responses, participants were asked follow-up questions to further elaborate using examples and user stories. This approach helped in obtaining thick descriptions that facilitated the conceptualization of stress-causing EHR design features (Warren 2002).

There were 3 in-person interviews while the rest 21 were conducted online using a video call application, in compliance with the revised IRB interview guidelines during the pandemic. Both in-person and video call interviews were recorded with the participant's consent. None of the participants refused to grant permission to record. Each participant was asked the same question in the same order. Recorded responses were transcribed using the natural language processing feature of a password-protected application with approximately 85% accuracy. Automated transcripts were further reviewed and corrected manually to achieve 100% accuracy. The hybrid method involving both application-based transcriptions followed by manual corrections reduced transcription time, significantly.

Qualitative Data Analysis

In-depth physician responses from at least 10 sub-specialties were analyzed using coding techniques (Miles and Huberman 1994) to develop issues, themes, and concepts that induce stress among physicians. This was an inductive process wherein extracted corpus was read multiple times iteratively that led to the identification of emerging categories (Corbin and Strauss 2014). Initial readings helped familiarize with potential elements and themes that may unfold while subsequent readings helped in the development of increasingly refined design issues, themes that are nested within structured mappings of IS design concepts based on information systems development fundamentals (Hoffer et al. 2015; Matook et al. 2021).

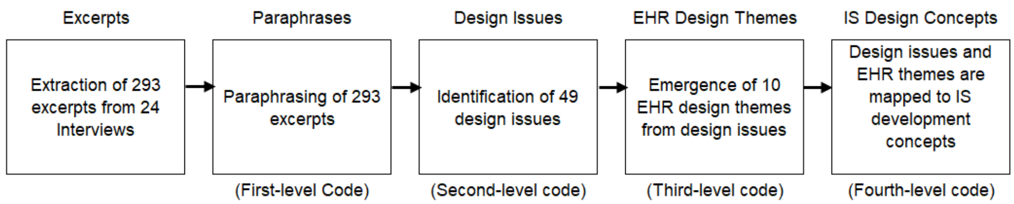


Figure 3: Coding Process for Analyzing Physician Interview Responses

We analyzed interview data in four levels as illustrated in Figure 3. The first level of coding involved a careful interpretation of the excerpts from interview responses and developing paraphrases to summarize the core idea that is being conveyed. Second, from the paraphrases, we identified issues and that are related to EHR design and indicative of causing stress. It is at this step, that we eliminate the several other themes of inquiry and focused only on paraphrases that appear relevant and robust to EHR design. For example, if a physician talks about the need to teach EHR in medical schools, it is not considered a design issue and thus excluded from the analyses. Third level coding involved a cautious examination of 51 design issues and then classifying them into themes that are representative of system design in the context of EHR. This step resulted in the emergence of 10 EHR design themes that afford stress among physicians i.e., designed for business not medicine, specialty-specific system requirements, EHR inefficiency, unorganized data, functional deficiencies, readability, interoperability, vendor support, hardware and connectivity, and technical inabilities. Fourth, with a pragmatic epistemological standpoint, we triangulated the identified issues and themes with to system analysis and design concepts. This step analyzes which aspects of EHR system development fall short within the boundaries of technostress among physician users so that EHR vendors can use this information to design better information systems.

In summary, we followed a well-defined and structured coding approach that is suggestive of the rigor of our method and the validity of the inferences drawn.

Appendix O, exemplifies how the coding process resulted in the development of seven main EHR themes and how design issues and EHR design themes are mapped to IS design concepts derived from system analysis and design fundamentals. It also consists of a sample of excerpts from participants' responses alongside the interpretation for verification and consistency. Overall, we follow a rigorous qualitative analysis to conceptualize 10 design themes that unravels the unexplored role of information system design in affording stress among users.

Results: Stressful EHR Design Features

1. Designed for Business not Medicine

EHR's are more geared towards achieving billing objectives like coding of diseases and providing additional documentation and explanation supporting treatment plan and therefore they are a huge source of stress and dissatisfaction among physicians.

> *"I still never understood why we did our own billing and it's always been that way. They just don't want to hire people to do it and so frequently. And that's another interesting point that I should probably make. Just as you're talking about the technostress of the E.H.R, if we generated a note say. For our encounter today and we submitted that and we had our internal reviewers who were looking at core measures and all of the appropriateness of the billing. I would probably say on any given week for me at a minimum I would have two sometimes three or four requests from our reviewers to say well you didn't write. You didn't specify X Y or Z or you know can you be clearer about this. And so again even though I wrote it and I was pretty sure I spelled out things like I was not vague even though I wrote things sometimes we didn't write it the way that they wanted it written to be able to make sure that the billing was appropriate. So, we would also have that added element of like OK. You've got to go back. You've got to look at this chart again. You can you go back. Can you redocument. Can you make an addendum? So, you add that on to again a record that's so full of information. But it wasn't it wasn't written the way that they needed that spun. And so again if there's a way to sort of generate. OK what is the standards of how we should document these things upfront. Then we all are spending 14 you know. I mean if you if you actually answered one of those coding queries 15 to twenty minutes of your day is gone. Going back through trying to*

make it better. And if you do those three four five times a week you know there's just always there was always a patient who has been waiting".

(Hospitalist 4)

For example, if a patient has diabetes, for a hospitalist, it is the only information they need for the treatment plan. But from a billing standpoint, they have to document if they require insulin, if they have any complications, if they have kidney problems, if they have circulation problems. These granular details are not as important to a hospitalist as they may be to a primary care physician. This is because hospitalized patients are not going to be treated for their diabetic retinopathy or neuropathy. But a hospitalist is still required to document these details, which cannot be easily accomplished within the EHR systems.

Physicians are stressed with the additional documentation requirements that do not change the overall medical management of the patient and due to the added workload physicians end up working outside their regular hours. This impacts their well-being and evoke a sense of dissatisfaction.

The design issues discussed in this theme can be addressed by structuring system requirements and improving the process modeling to design an EHR that closely follows physician work flow.

2. Specialty Specific System Requirements

EHR's have either 'too-much' or 'not-enough' information for physicians and therefore we assert that vendors should disrupt by designing specialty-specific EHR systems. This endeavor would involve balancing standardization and customization based on requirements that are unique to each specialty vs those common across all physicians. For example, family medicine and internal medicine physicians work with historical patient data while that kind of information is not of great value to emergency room physicians. In the same vein, templates can help family medicine physicians work faster but for obstetricians use of copy-paste-template-driven notes are prone to losing the nuances that are important to capture during the monthly prenatal visits. Simple design issues like impractical dosage calculations done by EHR for pediatric patients and, while ordering insulin pens internal medicine doctors are unable to order a whole vial or an insulin pen but the EHR system instead need the order to be placed in mls. These design issues examples highlight the unique system requirements of sub-specialties that if met, can tremendously improve physician satisfaction with EHR.

> *"So, I think the simple answer is that I think you need to hire physicians probably from every specialty. Yes. Different. And what I need as a blood sugar or internal medicine doctor is not what the surgeon needs. Like they don't look at any of that stuff or compare to the Gyn doc. I mean it's so different what each screen means that if you're building an EMR you have to build it one to tailor to each specialty and what they look at but then still be able to incorporate the surgical needs to pull into a note that we can read together and say oh yeah that makes sense. You know I think the outpatient EMR is a totally different beast because it just clicks in completely differently. But at least from an inpatient perspective sitting there and like I said I mean why are there 16 different options for one medication like just have one or when you're building those plans build it with that with that. I mean whether it's surgery or me or did we just we're all going to need some of the same things or some parts that you build are going to be the same. But as far as notes and what key instrumentation things that I need to do my daily workflow is going to be different. Yes. It's going to be a really big endeavor".*
>
> (Hospitalist 1)

These design issues can be addressed by structuring system requirements, improving the process modeling, and designing customized interfaces and dialogues such that an EHR works for sub-specialty physicians.

3. EHR Inefficiency

The most common design issue that physicians find stressful is the umpteen number of clicks required to get to a screen and moving across the screens back and forth. For example, ER physicians refrain from prescribing narcotics because their ordering involves multiple steps that end up taking a lot of time which is of great essence in the emergency room environment. In addition, when physicians type the diagnosis as diabetes there is another pop-up for insulin or not insulin and then another pop-up is with complications without complications, then another pop-up is controlled or uncontrolled for which they have to write hyperglycemia. These multiple clicks annoy physicians while for some physicians entering this granular information does not change the medical management of the patient. Overall, EHR doesn't replicate how a physician thinks or would deliver care and this may impact quality of care.

> *"I think the detail is more I think it's actually more volume because when you see all those buttons there and your body wants to answer all the questions even if maybe it doesn't even apply. You find yourself answering questions that you never would have thought to ask if you were just interviewing them and writing a note. But because it's right in front of you go there. So, I think that causes some inefficiency. I think more with younger physicians than with more experienced physicians".*
>
> (Primary Care Physician, Family Medicine 1)

The above-mentioned design issues can be related to structuring system requirements and designing better user interfaces that can save physicians time.

4. Unorganized Data

Another common EHR design that affords stress is the overwhelming amount of information on the screen that is described as 'clutter' and 'visual noise' that consumes physicians' cognitive energy until they become, they their muscle memory kicks in that help them filter out the visual noise. In addition, due to the pandemic, new variables are amassing into the EHR but it is not organized in a way that can present the full clinical picture of a patient promptly.

> *"The point is there the access to the information but trying to navigate it is just so overwhelming...It's almost it's almost the they've given us so much that we don't even know what's helpful anymore. You know there's a set of things that I needed every day to take care of my patient. And potentially again if I had gone and started trying to get help and asking if maybe they could have reorganized maybe there was a structure to it".*
>
> (Hospitalist 4)

> *"I often encounter a lot of physicians who are more so frustrated with things that are templated and the structure of documentation because they feel like it is directly linked solely for the purposes of billing, that all the data that we are amassing and putting into a note and*

it becomes this this novel, if you will, essentially drive the insurance part or the billing part, and they don't feel like it necessarily may translate into quality, into better patient care"

(Specialist, Infectious Diseases 1)

This stress-inducing EHR design theme is related to structuring system requirements that relate to better process and data modeling and designing better databases, interfaces, and dialogues.

5. Functional Deficiency

Besides poor search function as highlighted in Table 1, EHR is also criticized for its inability to auto-fill information or reconciling medications from other providers. In addition, the majority of the physicians expressed dissatisfaction over federal requirements of quality measures not built into the system. Workarounds to address such functional deficiencies using templates is a hard and a major source of stress among physicians.

"I find the user interface pretty good but it's simple things like if I for example, if I'm ordering medications to go home with the patient if I want insulin, I want a specific type of insulin. It'll bring up 32 different insulins even if I put that number like the name of the insulin that I want. So, then you're going through each one trying to find the one that you want. the system a certain way. And they don't have doctor brain And I don't know what the redundancy of these things are or before if I wanted a specific medicine. It's a data entry person that put it into. So, when I'm ordering something, I'm putting it in the doctor way and it doesn't pull up. So, you're looking. Trying to figure out OK well how do I order this test or how do I order this panel. What did they put it under? So, it's not intuitive for like what doctors speak as we go through all this medical terminology stuff and putting it into the computer and like it's not that. OK well what's this or what's this"

(Hospitalist 1)

"Something that occurs to me is when all the quality measures that we are required to keep up with by the federal government aren't always built in to the EHR. And so we have to build work arounds. We have to kind of try to build something within our own templates that remind us to do the things that we need to do to keep up with our preventive measures and quality measures. And that can be a real struggle sometimes when the system you know it's designed to help remind you. But then when there's something that you're supposed to be reminded to do that your system doesn't do then you're having to try to retrofit your system to do what you need. And that can be really hard".

(Primary Care Physician, Family Medicine 1)

The design issues under this theme can be related to structuring system requirements and system maintenance.

6. User Interface

Poor readability in terms of features like wording, organization, and highlighting can also manifest as stress among physicians. For example, an infectious disease specialist has to look at an intensive amount of granular culture data every day, and therefore menu design issues like small font size, absence of breaks and lines, color-coding, and highlighting can cause stress and fatigue. These design issues can be addressed by designing a better user interface.

> *"So, I think visibility is difficult. I think looking for the details that you need specifically to perform whatever your job is within the health care system and trying to find those things, everything tends to be in the same font or the same size without maybe a lot of bold for the areas that you're looking for. So, I think it also becomes kind of a hunt for looking for what you need. Pretty much all those things, really, for me, it's readability like there's just there's so much data there and I'm a person with a specialty that I like having a lot of data, but in a way that is readable and it seems sometimes very cluttered in a lot of EMR, EMR systems to be able to do that"*
>
> (Primary Care Physician, Family Medicine 2)

7. Interoperability

Limited or no system interoperability with other hospitals, clinics, and insurance companies can also be a stressor. With the advancement in technology, physicians expect medical devices like patient monitoring, ventilators, etc. to interface with EHR and autofill data in the EHR. The absence of such capabilities affords stress and dissatisfaction among physicians that spend hours doing manual labor. In addition, certain specialties like pediatrics have to work with multiple other software packages, besides EHR and thus experience stress arising out of the use of multiple usernames, passwords and going back and forth between different systems.

> *"The connect the sharing of information between different systems is not perfect by any means. There are times when I can see into other systems and there are times*

when I cannot. So, I guess the lack of interconnectivity add some stressors at times".
(Primary Care Physician, Family Medicine 1)

These interoperability-related design issues can be related to structuring system requirements.

8. Vendor Support

Physicians are the primary users of EHR and thus are best positioned to provide feedback on system improvement. Most often physicians do not have time to initiate a system improvement request and this lack of support and inability to be heard can also cause stress. Physicians expect the presence of real-time incident reporting and feedback posting via hyperlinks that connect immediately. In addition, longer lead times in vendor support can also cause stress. These situations arise when the problem is beyond the control of internal IT support staff and thus places a demand upon external IT support. Designing EHR with better access can be related to the concept of after-sales support for users.

> *"Well our local I.T. group is very easy to work with very responsive. You know once we get to outside of our own institution the responsiveness decreases because it's not, you're not you know you're contracted with them but they're not really on the same team. And so, kind of what feels like an emergency to us may not necessarily be a high priority for them".*
> (Primary Care Physician, Family Medicine 1)

9. Hardware and Connectivity

Few physicians have expressed that hardware and connectivity limitations of old hospital buildings inhibit users to utilize EHR to its full potential and thus induce stress. The hardware and connectivity limitations also need to be kept in mind while designing EHR and can be addressed while structuring system requirements.

> *And I work in a hospital that was built in like. Nineteen fifty something. So, the electrical part of it trying to make this older hospital more Internet capable. It's gonna be harder because the wiring is older. You don't know what's been built around the area since then. So yeah. Technology's great to incorporate into medicine but not all areas of a city or even set up the same to handle that kind of technology*

capability. So, you can't just push an EMR system onto a physician and then it's not like it's like 17 other separate things that they have to do just or maybe write a 50-minute office visit. So, or a 30-minute note for the hospital. So that's where it gets a lot a lot harder

(Hospitalist 2)

10. Data Structuring Limitations

Finally, many physicians get stressed when they are unable to find a button for patients' words on the EHR and thus feel EHR generated patient note lacks personality. They also point out that, use of EHR and template-driven documentation generates generic-looking medical records that quite often miss out on minor yet important nuances. This may not be a design issue, yet it is a critical opportunity for innovations in EHR design.

"I mean I think that I actually capture more in the EHR. It's more generic. It's less there's less character. I think you maybe you don't get the essence of the personality of the patient because you don't quote the patient as much. You don't you know tell you. I would I would just use that. You don't use the patient's words as often. You click a button you know you translate the patient's words into a button you know. So, I think I think something's lost as far as the kind of..."

(Primary Care Physician, Family Medicine 1)

Discussion

Physicians are the central actors in the care-delivery yet EHR's are not designed keeping physician workflow in mind. It is important to note that there are important implications for designing an efficient system that is capable of mitigating technostress among its key users. First, in case of EHR's, it is expected to increase physicians' and nurses' job satisfaction. Secondly a system that is designed to cater to a specialty-specific clinical workflow is expected to have high usability and thus afford more accurate and complete patient records that can help with improving patient care and quality. In addition, EHR's that affords its user to document medical record nuances can positively impact physician satisfaction. Third, designing efficient systems can foster eustress among physicians such that they can see more patients which means reduced waiting time for patients.

Most importantly, this study unravels the importance of designing EHR's that are customized to sub-specialty workflows. A generic EHR is not enough for pediatrics as their requirements are unique in terms of developmental screenings, AAP (American Academy of Pediatrics) guidelines, immunizations, and birth history requirements. In addition, while a pediatrician can work with a computer during a patient encounter an obstetrics and gynecology doctor cannot. Time is of the utmost importance to an emergency care physician and most often they are not interested in patient history from 20 years ago, which is of high value to a primary care specialty. EHR's have every option under the sun while most of it is not relevant to a general surgeon who will be happier working with a trimmed down version that includes elements like referring doctors, labs, scans, and pathology. Even the highly specialized systems geared specifically towards oncology can be tricky and lacks critical functionalities that can lead to medical errors that may be life-threatening. Overall, failure to emulate and integrate the complex specialty-specific clinical workflow of the central actors of care delivery can lead to a myriad of ramifications like poor usability, diluted medical records that lead to technostress among physicians.

Conclusion

With the recent pandemic, healthcare is in the spotlight revealing the plight of front-line workers and the stressful environment they work in. In this vein, it is unfortunate to note that information systems increase their workload and stress. Drawing on the theoretical foundations of the technostress phenomenon, we present a context-specific conceptualization of information system design features, themes that afford stress among healthcare users. To the best of our knowledge, extant literature has no information on stress affording design aspects of information systems and thus this work leverages the first-hand information gathered from physician interviews to examine EHR-driven technostress phenomenon and present a rich understanding of design themes and concepts that can be used by EHR vendors to design better information systems.

CHAPTER IV

ESSAY 3: SIMULATION-BASED EHR USABILITY EVALUATION: A PROOF OF CONCEPT

Introduction:

Poor usability of EHR solutions has been linked with physician burnout (Melnick et al. 2020). Further, poor EHR usability can potentially impact patient safety outcomes (Howe et al. 2018). The ONC 2015 edition EHR certification requires evidence of user-centered design (UCD) and user test results. However, the EHR system development and implementation process falls short in usability testing (McDonnell et al. 2010) as it is one of the most difficult criteria to complete for EHR vendors (Ratwani et al. 2015). It is also discussed that EHR usability evaluation can be standardized using objective metrics such as the number of clicks, time to complete tasks, and error rates because it can help EHR vendors identify usability issues resulting in an enhanced version of the system (McDonnell et al. 2010).

Improved EHR usability is shown to significantly reduce cognitive workload among physicians (Mazur et al. 2019). Although, EHR vendors are increasingly incorporating UCD, there is a significant gap in the validity of their usability evaluation results as the test cases may not represent the real clinical scenarios (Hettinger et al. 2021; Ratwani RM 2020). To this end, there is a need to devise improved usability evaluation methods that go beyond traditional instruments such as System Usability Scale (SUS) (Hettinger et al. 2021).

Further, it is noted that objective evaluation of digital solutions is one of the pressing problems in digital healthcare and a recent article (Guo et al. 2020) has called for the use of innovative methods in this domain. Oztekin et al. (2013) used machine learning algorithms to evaluate the usability of eLearning systems. They devise a severity index to rank the system characteristics that are most pertinent predictors of system usability that can eventually be used to identify features that need improvement. However, this work also utilizes perception-based survey data for model development. To this end, Guo et al. (2020) suggest utilization of simulation techniques to incorporate objectivity in usability evaluation methods. We build upon this gap and attempt to present a proof of concept that is capable of objectively evaluating the usability of EHR systems using simulation techniques.

Thus, our main research question is *how can we use simulation techniques to evaluate EHR usability?* In this work, we build a proof-of-concept (PoC) model that simulates an Emergency Department (ED) operations using discrete event simulation technique. The results of the model produce metrics such as clinician utilization, and idle-time that can be treated as objective measures of EHR usability evaluation the clinical department level. Our proposed PoC solution can be a quick and cost-effective solution to objectively evaluate an EHR usability and determine if it is delivering operational value at a clinical department level.

Literature Review

Usability is defined as the effectiveness, efficiency, and satisfaction with which users can accomplish goals in particular environments; the capability to be used by humans easily and effectively; quality in use; how easy it is to find and use the information displayed on a web-based system; ultimate quality factor for software architecture (Oztekin et al. 2013). Usability evaluation can be either *formative*, i.e. conducted during the iterative systems development or *summative*, i.e. post-hoc kind of testing of completed systems (Kushniruk and Patel 2004).

While subjective methods such as SUS (Brooke 1996) have been utilized widely in the usability evaluation of EHR's, it does little help with the continuous improvement of EHR design and user satisfaction (Ellsworth et al. 2016; McDonnell et al. 2010). Other methods like pre-post implementation evaluation are common too (Ellsworth et al. 2016), however, they are time and cost intensive (Guo et al. 2020) and inflexible with respect to understanding why the system fails the assessment (Kushniruk and Patel 2004).

Recent literature in healthcare has extensively focused on usability evaluation of EHR systems. Sinsky et al. (2020) proposed core EHR use measures that reflects a practice efficiency – total EHR time, work outside of work, time on encounter note medication, time on prescriptions, time on inbox, teamwork for orders, undivided attention. Ellsworth et al. (2016) utilized a systematic review to highlight the most common methods utilized for evaluating usability of EHR's – survey, think-aloud, interview, heuristics, cognitive walkthrough, focus group, task analysis and clinical workflow analysis. Among these methods, type of evaluations used are – pre-post implementation, prototype, requirements/development and mixed. They also highlight that only 23% of the studies report objective data such as time to task completion, task completion accuracy, usage rates, mouse clicks, and cognitive workload.

Thus, there is dearth of research that present scientifically valid and reproducible evaluation of usability for various stages of EHR system development (Ellsworth et al. 2016). In addition, there is a need to move towards EHR design and usability evaluation that focus on the "socio-technical" and "human factors" aspect of it (Carayon and Salwei 2021). We argue that this can be achieved by simulating the real-world clinical settings and developing models that are capable to evaluating EHR usability.

A simulation is the imitation of the operation of a real-world process or a system over time. It can be used to investigate a wide-variety of 'what-if' questions about a real-world system by using mathematical models based on probability theory. Use of simulation techniques is ideal in case of complex system behavior involving humans, experimentation costs are high, time and resources are limited. Thus, it can be used to predict the performance of a system at the early design stage thereby saving costs that may arise out of post-implementation evaluation and improvement efforts (Banks et al. 2013).

Research Design

Our main research question is *how can we use simulation techniques to evaluate EHR usability?* For preliminary results, we intend to utilize the task-time data published in physician workflow/ time-motion studies to approximate the task distributions and based on them, build a simulation model that is capable of assessing the usability of an EHR system. Several studies have reported different specialty clinician's EHR task-time data, for during and after regular working hours (Adler-Milstein et al. 2020; Arndt et al. 2017; Asan et al. 2015; Ballermann et al. 2011; Carayon et al. 2015; Hefter et al. 2016; Kim et al. 2012; Overhage and Johnson 2020; Sinsky et al. 2016; Tipping et al. 2010; Young et al. 2018). Based on this data source, we plan to identify task-time distributions for clinical workflows of emergency department, pediatrics, family medicine, oncology and intensive care units.

We will follow the standard simulation model development methodology that includes 11 sequential steps i.e. problem formulation (determining the scope); setting of objectives and overall project plan (justifying if simulation is the right method to for the problem at hand); model conceptualization; data collection; model translation using a tool like Simio, Excel or C++; model verification (to check if model is coded correctly); model validation (to check if model represents the real system); experimental design (to check the alternatives); production runs and analysis; conducting more runs (to have tighter CI); and finally documentation and reporting.

Model Development: A Proof of Concept

We aggregate the above simulation model development methodology into four key steps, as discussed below (Joines and Roberts 2015). By doing so, we present an example proof of concept simulation model that shows how we can use discrete event simulation techniques to evaluate usability of an EHR system at a clinical department level. Below we model an example workflow of an emergency department.

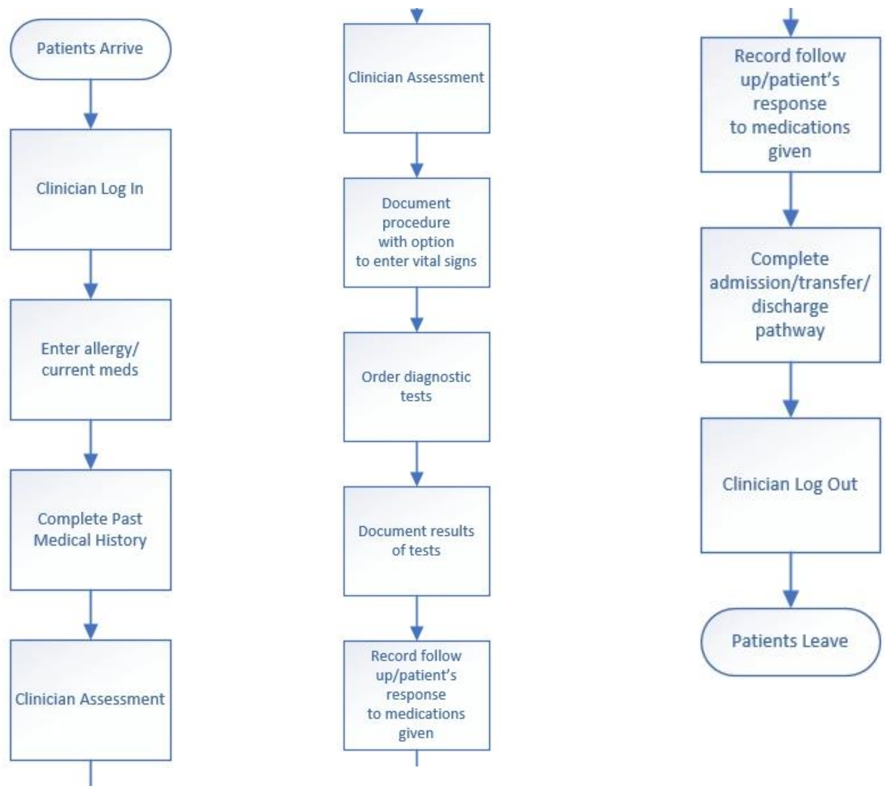


Figure 4: Physician-EHR Interaction Flowchart of an Emergency Department - Based on Kim et al. (2012)

Step 1: Problem Formulation, Objective and Plan

We illustrate a proof of concept simulation model that can be used to evaluate the usability of an EHR system at the specialty or department level. Using Simio®, we model an emergency department with four clinicians or resources that serve patients using an EHR system. Since, a clinician works in tandem with other clinicians in utilizing EHR, we believe an individual department level is the most appropriate to assess whether an EHR system is useful or not. To this end, we argue that simulating the real-world setting to test the usability of a system seem more than reasonable.

We limit the scope of our model to the activities of four clinicians that each work 40 hours per week. Simulation models can make several assumptions to incorporate the complexity of the care delivery process such as requirements of two clinicians at the same time for service delivery. However, to allow for PoC simplicity, we only assume the possibility that a clinician is needed before the patient is serviced.

Step 2: Model Conceptualization and Data Collection Plan

We conceptualize our model using an example physician-EHR interaction flowchart (Figure 4) of an emergency department (Kim et al. 2012). The example workflow illustrates typical set of tasks an Emergency department physician will carry out using an EHR system. Each of these tasks will have an estimated time duration which can be captured either by using observational methods (Asan et al. 2015) or EHR log-data (Sinsky et al. 2020). An example of data collection format is presented in the Appendix Q. Preliminary results can be obtained by using appropriate workflow mapping and approximate task-times from published literature as shown in Appendix Q.

Step 3: Model Translation Using Simio®

We make following assumptions to develop translate our conceptual model in Simio® as shown in Figure 5:

- Patients arrive exponentially with an interarrival time of 6.5 minutes
- Service time follows a Pert distribution with a minimum of 60 mins, maximum of 120 minutes and a mode of 90 minutes

- Clinician resources have a reliability logic set up that allows clinicians to respond to emergency calls. Uptime Between Failures follow an exponential distribution with a mean of 6 hours and Time to repair follows a Random.Pert(40,55,60) distribution
- Capacity of the clinician server is not constrained, i.e. set to infinity
- List of resources is created from which the model can pick
- Patients can request a specific clinician and then after service the clinician will be released

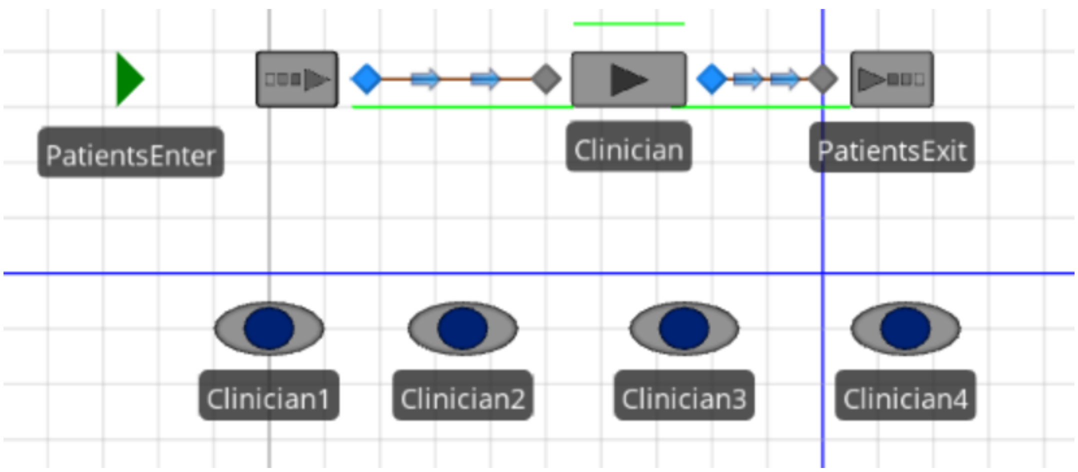


Figure 5: Simio® Simulation Model of an Emergency Department with Four Clinicians

Finally, the model is run for 40 hours and example results are reported in Table 10 and 11.

Step 4: Model Verification and Validation

Model verification answer the key question- Does the simulation model behave the way we expect? This can be achieved by tweaking the various model assumptions and observing changes in the output metrics. For example, longer processing time should lead to longer times in the system.

Model validation answers the key questions- Does the simulation produce performance measures that are consistent with the real system? This can be achieved by developing a model that closely approximates the factors that impact our output metric of interest. In our case, our output metric of interest is resource utilization. We want optimal utilization of clinicians. If a clinician's utilization is more than 100%, they are working outside of their regular working hours, implying that the current EHR system may not be usable for the clinician. Therefore, it will be imperative for our model to 1) closely map each specialty-specific EHR workflow task sequence, and 2) obtain valid EHR-related task-time measures.

Example Results

Our proof of concept EHR usability evaluation model for an Emergency department was run for 40 hours and clinician server statistics are reported in Table 10, with a total of 97 patients being served in a week with an average processing time of 1.5 hours for each patient. Clinician utilization metrics for all four clinicians are reported in Table 11 with a grand mean clinician utilization of 93.23%. Simio results screenshot is reported in Figure 6.

Table 10: Clinician Server Station Processing Statistics

	HoldingTime InStation (Average)	HoldingTime InStation (Max)	HoldingTime InStation (Min)	TotNum Entered-Throughput	TotNum Exited-Throughput
Clinician Server	1.50 hours	1.95 hours	1.1 hours	101	97

The results can also be used for model validation. For example, 20 patients /day in an emergency department seem to be a reasonable approximation of reality. However, the inter-arrival time of 6.5 minutes could need further validation as it seems very high for an emergency department.

Table 11: Simulation Results for EHR Usability Evaluation

	Utilization (%)	Patients Served	TimeBusy (%)	TimeBusy (hours)	TimeIdle (%)	TimeIdle (hours)
Clinician1	96.8%	25	87%	34.8	0.01%	0.006
Clinician2	90.60%	25	84.10%	33.64	0.22%	0.09
Clinician3	94.22%	27	89.46%	35.78	1.33%	0.53
Clinician4	91.30%	24	84.17%	33.66	2.57%	1.03
GrandMean	92.23%	25.25	86%	34.47%	1.03%	0.414%

Clinician utilization results from Table 11 can be used to comment on whether an EHR system is forcing the clinicians of the department to work outside of their capacity. For example, if a clinician is busy 90% of the time and only has few minutes of idle time during the day, it indicates that the clinician user is overworked by the use of EHR. This is against the standard operations wisdom that 100% labor utilization is not optimal.

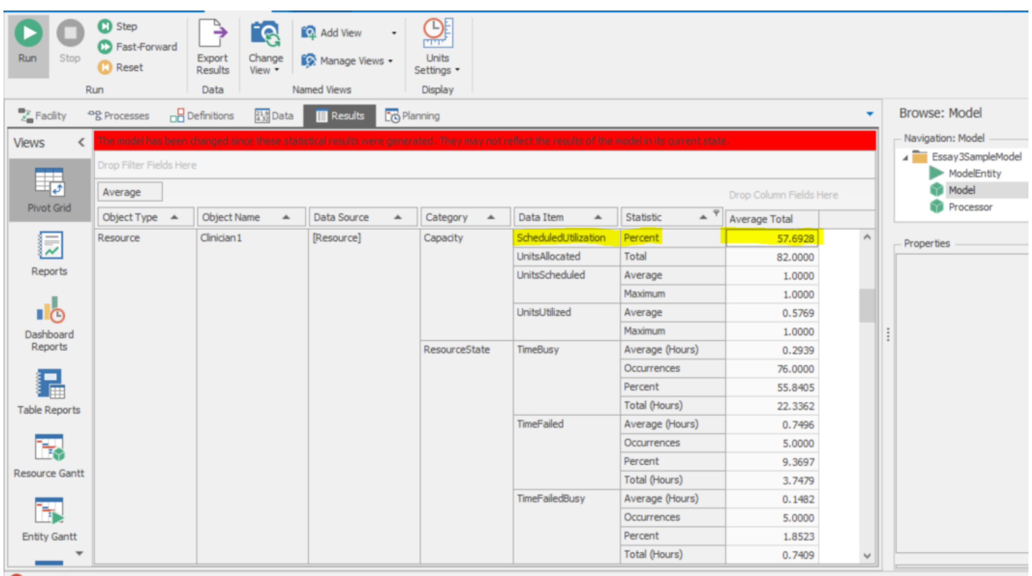


Figure 6: Simio® Simulation Model Results Screen

Projected Activities

As next steps, we intend to conduct a detailed literature review to collect and validate the published data on physician workflow sequence of tasks and the corresponding task-times. Once we have a large enough sample size, a simulation model will be developed as shown in previous sections. The outcome of the model in terms of efficiency and utilization metrics of clinicians can serve as a proxy to evaluate the usability of the electronic health records.

In addition, we intend to develop the simulation-based usability evaluation models for each clinical specialty. This will allow for better model verification and validation. Finally, we also plan of increasing the complexity of the model by using task-sequences within the server processing station that will further enhance the model validity that concerns evaluation of EHR-usability.

Expected Contributions

This work is intended to be a proof of concept that is aimed to pave the road toward more comprehensive simulation based quantitative studies to better understand and improve EMR system usability. First, we expect our results to help open a new avenue for using simulation-based techniques to objective evaluate EHR usability. By doing so, we can determine whether or not, an EHR system is able to deliver operational value for a clinician within a clinical specialty. Second, this method of usability evaluation can bridge the gap between the conflicting results of qualitative and survey-based quantitative evaluation methods (Zheng et al. 2010). Third, simulation-based usability evaluation can be a substitute to time-motion based pre-post evaluation methods which are costly, time-consuming and often of little use as they are conducted post-implementation (Guo et al. 2020). Finally, with the increasing popularity of digital health solutions and IOT in healthcare, this method can be used to evaluate the usability of other digital health solutions.

In summary, healthcare IT is touted as the most promising fix to the problem of high cost of healthcare in United States. However, poor usability of EHR systems has contributed to physician dis-satisfaction and burnout (Melnick et al. 2020) and thus it is important to find better methods to evaluate the usability to EHR systems. In the absence of a formal and standardized EHR usability evaluation tools and techniques, it is difficult to achieve optimal EHR design and thus research work done to fill this gap will help in moving the field of usability evaluation in a positive direction.

CHAPTER V

CONCLUSION

As of 2019, healthcare expenditures in the United States represented 18% of its Gross Domestic Product (GDP) and yet ranks below the Organization for Economic Cooperation and Development (OECD) average in health outcomes. Of the total US$ 3.3 trillion spending, administrative costs account for 25% (Himmelstein et al. 2014), the highest among the eight most developed countries. These exorbitant figures will continue to grow as the baby boomers continue to retire with a Medicare enrollment rate of 10,000 per day. Containing the cost of healthcare is one of the top priorities for the federal government, researchers as well as businesses.

The high cost of healthcare is mainly attributed to a fragmented delivery model with misaligned financial incentives, resulting in excess expenditures, low patient satisfaction, poor care quality and inefficient care delivery (Nattinger et al. 2018). A decade ago, Bodenheimer (2008) discussed overstressed primary care, lack of interoperable computerized records and lack of integrated systems that facilitate care-coordination among the major barriers to seamless care coordination.

Today, not much has changed, Doty et al. (2020) finds that US physicians did not routinely receive timely notification or the information needed for managing ongoing care from specialists, after-hours care centers, emergency departments, or hospitals and that there is a lack of electronic information exchange outside the practice. This finding directly connects the dots with the practice of information blocking which indicate that healthcare providers are reluctant to share patient information with their competitors (Everson et al. 2021).

First essay of this this dissertation addresses the current problem of information blocking and provides empirical evidence that providers can indirectly generate business value even when they exchange information with their competitors. Based on a proposed healthcare referral network model and the associated network externalities, our findings foster cooperation among disparate healthcare providers and supports the idea of sustained cooperation among providers facilitated through the adoption and use of interorganizational systems.

Concomitantly, the sudden rise in the adoption of EHR systems has worsened the existing problem of physician burnout. Mandatory use of inefficient EHR systems has forced physicians to work outside of their regular working hours (Adler-Milstein et al. 2020). The 2018 Physician Foundation Survey found that electronic health records (EHR) are the greatest source of professional dissatisfaction among physicians and that 49% would not recommend medicine as a career to their children, 17% plan to retire (up from 14% in 2016) and 12% plan to find a non-clinical job or position. This could have serious ramifications, in the face of existing physician shortages which is projected to reach 120,000 by 2030 (PhysicianFoundation 2018). Thus, the burgeoning problem of physician burnout will only add fuel to the already existing fire of high healthcare costs.

Enhancing the efficiency and effectiveness of the existing EHR systems with interoperability features is considered to be the preferred solution to reduce the physician workload in the long term. Nevertheless, an important aspect of EHR-driven physician burnout is to understand what specific design characteristics of these complex systems induce stress among physicians? The second essay of this dissertation investigates this novel research question leveraging the first-hand information from physicians and identifies fifty-one design issues that lead to the emergence of ten EHR design themes that can induce stress among physicians.

Our results provide a deeper understanding of the technostress phenomenon within the contextual setting of physician burnout. Most importantly, despite physicians being the central actors in the care delivery model and the availability of a generalizable workflow for each specialty, current EHR design does factor in specialty-specific workflow. Furthermore, and interestingly, physicians' also worry about the unintended consequences of structuring data that increasingly result in diluted patient records with limited variability. The latter raises critical questions in terms of the validity and veracity of EHR data and its ensuing impact on its increasing use in research and practice.

Thus, in the second essay we conclude that for successful digital transformation in healthcare, we need to design EHR systems that work in favor of their key users, while minimizing its unintended consequences.

Finally, our third essay is motivated with a premise that we need to design and develop EHR with better usability such that it minimizes the unintended consequences for its key users. In the absence of time and cost-efficient options to evaluate EHR usability (McDonnell et al. 2010) , we present a proof-of-concept that uses simulation techniques to evaluate EHR usability. We show with an example, that how the output metrics of a simulation model, such as clinician utilization, can be used to evaluate EHR-usability. As we move towards digital transformation and IoT in healthcare, it is important to test the digital solutions if they are worth the money, time, and energy spent in their purchase, installation, adoption, and use by scarce resources like clinicians.

Another common theme of the three essays of this dissertation is the emphasis on levels of care delivery- specialty and ambulatory care levels. The first essay addresses the care coordination between hospitals and ambulatory entities. The second essay, investigates stressful design issues among specialty and primary care physicians. In the same vein, third essay intends to develop task-time distributions and corresponding simulation models for specialty and primary care entities. Based on World Health Organization's guidelines on design and implementation of health information systems that discusses framework for designing health information systems (Lippeveld et al. 2000), we argue that it is important to capture the variability and commonalities that exists within and between these clinical entities.

Discussing the relationship between the health information systems and the macro-care delivery system, they suggest that "health information system structure should permit generation of the necessary information for rational decision making at each level of the health services system". They further describe the three levels of care: primary, secondary and tertiary. Primary care is the first point of contact between the patient and the population. Secondary level provides more specialized care like emergency care and diagnostic services while the tertiary care serves the population with highly specialized care like surgical care and related interventions. Suitably, academic literature has typically focused on choosing their unit of analysis from one of these levels. We argue that results from one level of care may not help in generalization for overall care delivery systems. This is because the workflow protocols are completely different in each of these care-levels. This should make intuitive sense as the experience at a primary care provider's office is different from an emergency room visit which is again different from a hospitalization experience for a surgical or long-term care treatment. Therefore, in order to gain complete understanding of electronic health records, the three essays carefully address the complexity of traditional organization of healthcare services and its implications on EHR use and impact.

Digital transformation is touted as the next most significant reform in healthcare, but the current public health landscape has made it a global priority. Addressing the burgeoning problem of information blocking and clinician burnout, this dissertation investigates and unravels interesting insights about the intended and unintended consequences of EHR use. First, we empirically show how providers can derive value by sharing information with its competitors. Since, focusing on bright side of EHR use paints an incomplete picture, we shift our focus to qualitatively explore how EHR design contributes in causing stress among physicians. We conceptualize ten stress inducing EHR design themes that vendors can use to design better information systems. Finally, in order to design better information system, we need better tools and techniques to evaluate its usability. To this end, we propose a proof of concept that utilizes simulation-based techniques to evaluate EHR usability.

Overall, this dissertation utilizes information systems theories and frameworks to address critical aspects of electronic health records. We believe this work can advance the current knowledge and understanding of HIT use and impact and contribute in helping IT succeed in healthcare.

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APPENDICES

APPENDIX A: Upstream and Downstream Spillover Effects in Healthcare IT

Cheng and Nault 2012

Supplier | **Customer**

IT investment —Upstream spillover effects due to intermediate inputs→ Productivity

Productivity ←Downstream spillover effects due to intermediate inputs— IT investment

Applying Cheng and Nault 2012 in HIT

Ambulatory Care | **Hospital**

IT Adoption —Upstream spillover effects due to patient referral→ Bottom-line

Bottom-line ←Downstream spillover effects due to patient referral— IT Adoption

APPENDIX B: Estimating the Volume of Information Exchange between Primary and Specialty Care

Potential Information Exchange between Primary and Specialty Care		
Total PCP Visits	% of Primary to Specialty Referral	Volume of Patient Exchange between Primary Care and Specialty Care Levels
481 million (CDC, NAMCS 2016)	5% (Forrest et al. 2006)	24 million referrals
Potential Information Exchange within Hospitals		
Total Hospital Admissions	% of interhospital transfers	Volume of Patient Exchange within Specialty Care Level
36 million (AHA Fast Facts 2017)	4% (Hernandez-Boussard et al. 2017)	1.44 million interhospital transfers

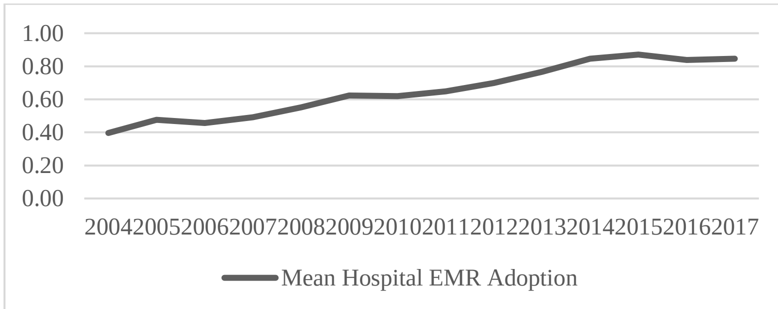
APPENDIX C: Summary of Literature Utilizing Ambulatory Care Level

Journal	**Author**	**Year**	**Context in which ambulatory care level has been studied**
Medical decision making	(Forrest et al.)	2006	Examined the **PCP's specialty referral decision making process** and found that 5.2% of all the visits result in specialty referral.
JAMA	(Kripalani et al.)	2007	A systematic review approach to examine the **deficits in the discharge information transfer between hospitals and PCPs**. They find often discharge summaries are incomplete and lack imp info like test results, t/t course, discharge medications, pending test results, patient/fam counseling and follow up plans.
Journal of Biomedical Informatics	(Frisse and Holmes)	2007	Projected financial savings associated with the use of HIE, based on literature-based assumptions. They suggest participation in HIE's can support the shift from emergency room to **clinical care.**
NEJM	(Bodenheimer)	2008	A commentary on the perilous journey of a patient through the healthcare system. Emphasizes the importance of **coordinating care between primary care and specialty care**.
Ann Int Med	(Adler-Milstein et al.)	2011	Surveyed 179 U.S.-based RHIOs to find the status of operational HIE's and found that 14% of US hospitals and **3% of ambulatory practices** were actively participating in the 75 operational RHIO's.
ISR	(Yaraghi et al.)	2015	Using a 3-year HIE data of 463K access logs, this study uses network analysis, to show that practices with a higher number of shared patients, larger market share, and higher dependency on major practices will adopt HIE faster than others. They discuss the multiple sides of an HIE as - patients, labs, radiology centers, hospitals, **private practices** and payers.
MISQ	(Ayabakan et al.)	2017	Investigated the impact of health information sharing on the extent of duplicate diagnostic testing, in the **context of outpatient clinics of hospitals**. Interorganizational information sharing is associated with a higher level of reduction in the duplication rate of radiology imaging tests compared to laboratory tests.
ISR	(Adjerid et al.)	2018	Operational HIE are associated with reduced Medicare spending in an HRR. Operational HIE is measured using Adler-Milstein et all 2011 survey data. They test HIE maturity mechanism under the assumption of the significant correlation between time an HIE is operational and the **percentage of ambulatory care facilities providing and receiving data through an HIE**

APPENDIX D: Operating Cost Categories as % of Total Operating Cost

General Services	44%
Ancillary Services	25%
Inpatient Routine Services	14%
Outpatient Services	7%
Non-reimbursable	8%
Other reimbursable	2%
Special Purpose	2%

APPENDIX E: EHR Adoption Trend



APPENDIX F: Spillover Effects by EHR Applications

	DV: log(Inpatient Cost/Discharge)				
VARIABLES	CDR	CDSS	CPOE	OE	PD
Focal EMR App	0.038***	0.032***	0.005	0.052***	0.000
	(0.010)	(0.008)	(0.004)	(0.015)	(0.004)
Focal EMR App (t-1)	-0.003	0.008*	-0.003	0.006	0.001
	(0.006)	(0.004)	(0.003)	(0.008)	(0.003)
Focal EMR App (t-2)	0.008*	-0.001	-0.005*	0.018**	-0.002
	(0.005)	(0.005)	(0.003)	(0.007)	(0.003)
Focal EMR App (t-3)	0.012**	0.013***	-0.002	0.021***	0.005
	(0.005)	(0.004)	(0.004)	(0.007)	(0.004)
Ambulatory EHR	-0.002	-0.003	-0.001	-0.001	-0.001
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Ambulatory EHR(t-1)	-0.000	-0.001	-0.001	0.000	-0.001
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Ambulatory EHR(t-2)	-0.018**	-0.018**	-0.018**	-0.019**	-0.018**
	(0.008)	(0.008)	(0.007)	(0.008)	(0.007)
Ambulatory EHR(t-3)	-0.035***	-0.035***	-0.035***	-0.034***	-0.036***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Observations	23,170	23,170	23,170	23,170	23,170
R-squared	0.529	0.529	0.528	0.530	0.528
Number of Hospitals	2,317	2,317	2,317	2,317	2,317
Hospital FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Notes: Hospital-level controls for the focal hospital and for the other hospitals in the HRR: log(Inpatient Days), log(Bed No.), log(Total FTE), Case Mix Index. HRR-level controls: Percent residents 65 years and older, Percent college graduate, log (Total population), log(Median household income). Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1					

APPENDIX G: Spillover Effects by Bed Size

	DV:log(Inpatient Cost/Discharge)		
VARIABLES	**Beds >=50**	**Beds >=100**	**Beds >=200**
Focal Hospital EHR	0.017**	0.011	-0.002
	(0.008)	(0.009)	(0.012)
Ambulatory EHR	-0.043***	-0.050***	-0.039***
	(0.009)	(0.010)	(0.014)
Observations	25,463	19,191	8,816
R-squared	0.579	0.523	0.446
Number of Hospitals	2,055	1,577	821
Hospital FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Notes: Hospital-level controls for the focal hospital and for the other hospitals in the HRR: log(Inpatient Days), log(Total FTE), Case Mix Index. HRR-level controls: Percent residents 65 years and older, Percent college graduate, log (Total population), log(Median household income). Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1			

APPENDIX H: Spillover Effects HSA Market

	DV:log(Inpatient Cost/Discharge)
VARIABLES	(1)
Focal Hospital EHR	0.062***
	(0.018)
Ambulatory EHR	-0.029**
	(0.013)
Observations	14,298
R-squared	0.461
Number of Hospitals	1,105
Hospital FE	Yes
Year FE	Yes
Notes: Hospital-level controls for the focal hospital and for the other hospitals in the HRR: log(Inpatient Days), log(Bed No.), log(Total FTE), Case Mix Index. HRR-level controls: Percent residents 65 years and older, Percent college graduate, log (Total population), log(Median household income). Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1	

APPENDIX I: Spillover Effects by Clinic Density Per 10,000 people

VARIABLES	DV: log(Inpatient Cost/Discharge)
Ambulatory EHR x Clinic Density	-0.015*
	(0.008)
Focal Hospital EHR	0.034***
	(0.010)
Ambulatory EHR	-0.014
	(0.013)
Observations	30,030
Number of Hospitals	2,310
R-squared	0.611
Hospital FE	Yes
Year FE	Yes
Notes: Hospital-level controls for the focal hospital and for the other hospitals in the HRR: log(Inpatient Days), log (Bed No.), log (Total FTE), Case Mix Index. HRR-level controls: Percent residents 65 years and older, Percent college graduate, log(Total population), log(Median household income). Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1	

APPENDIX J: Spillover Effects Pre-Post HITECH 2012 Implementation

VARIABLES	DV: log(Inpatient Cost/Discharge)
Focal EHR	0.036***
	(0.010)
Ambulatory EHR	-0.026**
	(0.011)
Ambulatory EHR X Post HITECH12	-0.033**
	(0.013)
Observations	30,030
R-squared	0.609
Number of Hospitals	2,310
Hospital FE	Yes
Year FE	No
Notes: Hospital-level controls for the focal hospital and for the other hospitals in the HRR: log(Inpatient Days), log(Bed No.), log(Total FTE), Case Mix Index. HRR-level controls: Percent residents 65 years and older, Percent college graduate, log (Total population), log(Median household income). Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1	

APPENDIX K: State/County/HRR/Year Fixed Effects

	DV: log(Inpatient Cost/Discharge)		
VARIABLES	(1)	(2)	(3)
Focal Hospital EHR	0.034**	0.023**	0.047***
	(0.013)	(0.010)	(0.012)
Ambulatory EHR	-0.031*	-0.037***	-0.033**
	(0.017)	(0.012)	(0.013)
Observations	30,030	27,014	17,132
R-squared	0.610	0.585	0.606
Number of Hospitals	2,310	2,078	2,310
State FE	**Yes**	**No**	**No**
County FE	**No**	**Yes**	**No**
HRR FE	**No**	**No**	**Yes**
Year FE	**Yes**	**Yes**	**Yes**
Notes: Hospital-level controls for the focal hospital and for the other hospitals in the HRR: log(Inpatient Days), log(Bed No.), log(Total FTE), Case Mix Index. HRR-level controls: Percent residents 65 years and older, Percent college graduate, log (Total population), log(Median household income). Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1			

APPENDIX L: Standard Errors Clustered at the HRR Level

```
. xtreg ln_tcperdis teremrratio2_c avgambuemr2_c $control, fe vce(cluster new_hr
> r)

Fixed-effects (within) regression               Number of obs     =     30030
Group variable: prvdr_num                       Number of groups  =      2310

R-sq:  Within  = 0.6103                         Obs per group: min =        13
       Between = 0.0359                                        avg =      13.0
       Overall = 0.0327                                        max =        13

                                                F(22,302)         =    200.77
corr(u_i, Xb)  = -0.9937                        Prob > F          =    0.0000

                              (Std. err. adjusted for 303 clusters in new_hrr)
```

ln_tcperdis	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
teremrratio~c	.0339604	.0108213	3.14	0.002	.0126658	.0552551
avgambuemr2_c	-.0313544	.012375	-2.53	0.012	-.0557066	-.0070022
logipdays	-.6097314	.0347108	-17.57	0.000	-.678037	-.5414258
ln_bedno	.0332504	.0224176	1.48	0.139	-.010864	.0773648
logtotfte	.286516	.0339222	8.45	0.000	.2197622	.3532698
cmiv	.072375	.0226901	3.19	0.002	.0277242	.1170258

Figure 1: Standard Errors Clustered at the HRR level

APPENDIX M: Multi-level analysis with FE for Independent Variables and Random Effects for Regional Intercept

```
Mixed-effects GLM                               Number of obs     =     33,397
Family: Gaussian
Link:    Identity
Group variable: hrrnum                          Number of groups  =        301

                                                Obs per group:
                                                              min =         13
                                                              avg =      111.0
                                                              max =        650

Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(22)     =    5137.91
Log pseudolikelihood = 15961.378                Prob > chi2       =     0.0000
                              (Std. err. adjusted for 301 clusters in hrrnum)
```

d_ln_tcgiapd	Coefficient	Robust std. err.	z	P>|z|	[95% conf.	interval]
d_teremr2	.0471536	.0107701	4.38	0.000	.0260445	.0682627
d_hrrambuemr2	-.0306191	.0129147	-2.37	0.018	-.0559315	-.0053067
d_ln_ipdays	-.571952	.0292612	-19.55	0.000	-.629303	-.5146011
d_ln_bedno	.0557832	.0292715	1.91	0.057	-.001588	.1131544
d_ln_fte	.1303453	.0180262	7.23	0.000	.0950146	.1656759
d_cmi	.0862339	.0226251	3.81	0.000	.0418895	.1305783
d_edu_year	-.0250467	.0160794	-1.56	0.119	-.0565618	.0064684
d_age_year	-.082425	.0328222	-2.51	0.012	-.1467553	-.0180946
d_inc_year	-.0030966	.0048427	-0.64	0.523	-.0125882	.0063949
d_pop_year	.0000259	.0000151	1.72	0.086	-3.64e-06	.0000554

APPENDIX N: Interview Script

Interview Script:

My name is Ankita Srivastava and I am a Management Science and Information Systems PhD student. This study is part of my dissertation work on Technostress and Physician Burnout. Technostress is the stress cause due to the use of IT systems and specifically, I want to look at what EHR characteristics contribute in Physician Burnout.

So, I will start by asking a few questions:

1. Do you feel burned out or stressed due to the use of HER?
2. Have you observed situations where other Physicians had experienced burnout due to the use of EHR or Information Technology?
3. Gender
4. Age
5. Specialty?
6. How many patients do you see in a week?
7. What % of your workday is spent working with EHR?
8. What specific EHR characteristics cause stress? (recall with screenshots)
9. Elaborate using example?

APPENDIX O: Identification of Research Gap in Technostress Literature

	What we know and care about	**What we dont know and care about**
I	*ICT Characteristics that influence technostress*	*What specific EHR usability characteritics lead to stress manifestations among primary and specialty care physicians?*
	Work Overload, Invasion, Insecurity, Role-ambiguity, Work-home conflict, Usefulness, Complexity, Reliability, Pace of Change, Presenteeism, Anonymity	Califf et al. 2020 has called for a qualitative inquiry to understand specific technology features that contributes to eustress or distress
II	*Individual Characteristics that influence technostress*	*What specific physician characteritics influence technostress related burnout*
	Technology Usage- more frequency, more affected	Is the system use more frequent in case of physicians?? Inherent volume of medical records and current knowledge management requirements
	Age-older folks more affected	To examine if age may not be a problem in future when technology natives enter the workforce
	Gender-Males more affected	If gender affords technostress among physicians
	Education- higher, less likely to be affected	Education is not a applicable as all physicians receive similar academic and practical training. However, years of experience with the EHR system may have an influence?
III	*Organizational Characteritics that influence technostress*	*What specific org-level characteristics influence technostress related burnout?*
	Involvement facilitation- higher the involvement in development process lower the technostress	What are the differences and similarities in EHR-driven stress manifestations among primary and specialty care level physicians - if an internal medicine physician is involved in the development process, EHR may have usability issues with other specialties. This is because the clinical workflow is different for different specialties
	Innovation Support- a culture of innovation reduces tenchnostress	Healthcare as an industry is heavily driven by innovation in medical technology. However, since EHR systems are mandated by the federal governement, organizational culture may not be a relevant factor in case of EHR-driven technostress. It is, thus, important to understand how technostress is afforded among primary care and specialty care facilities.

APPENDIX P: Development of EHR Design Themes and Mapping with IS Design Concepts

I) Designed for Business not Medicine

Well, you know. Right now, the focus is more on billing and making sure you know you capture the times and all that stuff. I would like an EMR which is just clinical. I mean it's just basically the focus is more than just clinical and nothing else. And then the billing and everything else you can make like a separate stuff that we don't even have access to. (Hematology-Oncology Physician)

Paraphrase	**EHR Design Issue**	**IS Design Concepts**
Current EMRs are more focused on billing. Physicians would like a pure clinical EMR and a separate system that can handle the billing	Designed for Billing Use not Medical Use	-Structuring system requirements

II) Specialty Specific System Requirements

There are some hard stops those designers put in there that don't fit your practice and being able to have just to be able to have some control over some of those hard stops that just end up being like a chair sitting in the middle of the room. Right in the middle of hallway. No one's going to sit there...but you can't move it...Sometimes the hard stops are helpful because it helps you meet your measure without having to use memory to remember to do it... If it's not something that you need it's just a hurdle...And just I think that control having a little bit more of control over those types of functions I think would be huge. (Family Medicine Physician)

Paraphrase	**Design Issue**	**IS Design Concepts**
Hard stops don’t fit practice	Hard Stops	-Structuring system requirements -Design of interface and dialogues

III) EHR Inefficiency

...So, you're basically looking on one tab to figure out what the sugar is another tab to figure out how much. And some was given a third tab to figure out how much did they eat that day. And nothing is kind of clustered together as far as points of care that be in a group entity even on EHR2 like if the patient is on TPN or if the patient is on some kind of tube feeding it's another tab over. It's not all clustered in one place... (Internal Medicine Hospitalist)

Paraphrase	**Design Issue**	**IS Design Concepts**
Points of care that go together do not appear together on the user interface and user has to go back and forth several tabs/screens to synthesize what has happened with the patient in the last 24 hours	Going back and forth multiple screens to reconcile information and then wait for pages to load	-Structuring system requirements -Designing Databases -Design of interface and dialogues -System Maintenance

IV) Unorganized Data		
…The person who has like a urinary tract infection is only going to have a urinary tract infection for like a week or two. But you know that should fall off automatically into the off of the system. But there's nobody who's going to understand that. I mean no one from I.T. is going to put an end date automatically on a UTI because they're not medically trained to recognize that. So, somebody who has an asthma attack versus somebody who has chronic asthma. You're not constantly for seven years have an asthma attack. You have asthma and you occasionally get flare ups of your asthma. But there is not an end date on that asthma flare up... So, when you have like in EHR1 when you've got the outpatient side connected to the inpatient side...So, this person got like a urinary tract infection listed from 2014 that's now going to transfer into my inpatient hospital note because they didn't bother to just get rid of it. (Family Medicine Hospitalist)		
Paraphrase	**Design Issue**	**IS Design Concepts**
Hospital systems taking over outpatient physician clinics – outpatient getting connected to inpatient creates another problem – medical history/past conditions do not have an end date to it and gets transferred to the inpatient hospital note	No end date for the acute conditions rolling over in patient history	-Structuring system requirements -Designing Databases -Design of interface and dialogues
V) Functional Deficiency		
So, for a surgical patient after surgery, it's important to know their intake and output depending on the type of surgery. But I had to like I mean I had to go on my day off which is fine. But I was literally sitting there putting in "dot-this" "at-this" trying to find the right HYPERLINK that would automatically pull the information in from the chart into my note. And that's difficult to do. I mean there's like over a hundred of these things and sometimes it would work...That's why can't...just have one phrase that that's intuitive. I shouldn't have to be like - @ intake and output; @ i and o; I & o; I and o; Oh, like ok...Well then you can just make your own and I can make my own. But is it going to correlate? And then when you guys do an update, I'm going to lose my stuff that I penned in because it's going to erase everything that wasn't already preset into the thing. (Family Medicine Hospitalist)		
Paraphrase	**Design Issue**	**IS Design Concepts**
Finding correct hyperlinks that pulls in patient information from chart into the physician note is a time-consuming task. If physician builds their own, a future update can erase it.	-Poor search function - to find hyperlinks -Updates erase the hyperlinks created by physicians	-Structuring system requirements -System Maintenance
VI) Readability		
I think looking for the details that you need specifically to perform whatever your job is within the health care system and trying to find those things, everything tends to be in the same font or the same size without maybe a lot of bold for the areas that you're looking for... for me, it's readability like there's just there's so much data there and I'm a person with a specialty that I like having a lot of data, but in a way that is readable and it seems sometimes very cluttered in a lot of EMR systems ... I know physicians, I think, who are so displeased. Maybe as so much data is there that they often don't utilize it...they just write a free text without any of the benefits or what we think are benefits from EHR because they feel like the readability is less (Infectious Diseases Hospitalist)		
Paraphrase	**Design Issue**	**IS Design Concepts**
-The way EMR presents data is not readable and appears like clutter. Physicians like having a lot of data, but in a way that is readable	User interface to highlight new growth/ cultures and improve	-Design of Forms and Reports

-Some physicians are so displeased with the amount of data that they don’t utilize that the scrap the whole thing and use free text. They are willing to sacrifice the benefits of EHR in order to improve the readability of the notes.	the readability of the microbiology tab	-Design of interface and dialogues
VII) Interoperability *Every insurance plan has a different formulary. EPIC's biggest thing was yeah, our system will check through the formulary. How often do you update the formulary through your system for each of these individual insurances…Like the computer system is supposed to be this magnificent thing that should be cross checking what they say their insurances with what their formulary is to make sure that I'm sending them home with something they can afford not me having to go onto Google and then try to find their insurance and then try to find their formulary and then try to figure out whether or not it's on the formulary (Family Medicine Hospitalist)*		
Paraphrase	**Design Issue**	**IS Design Concepts**
Physicians have to google to find patient’s insurance and then corresponding formulary to check if the prescribed drug is there or sit on hold with insurance company to get this information. If they don’t then it reflects negatively on their quality measure (prescriptions). EHR systems should be connected to the updated formularies that patient’s insurance plans approve.	Inability of the EHR to automatically connect to and update patient's insurance formulary	-Structuring system requirements

APPENDIX Q: Fifty-One Stressful EHR Design Issues, Ten EHR Design Themes, and IS Design Concepts

	Design Issues	**EHR Theme**	**Primary IS Design Concept**
1	Poor design	EHR Inefficiency	Structuring system requirements - Process
2	Designed for Billing Use not Medical Use	Overall Objective is Business not Medicine	Structuring system requirements - Process
3	EMR is not intuitive	EHR Inefficiency	Design of interface and dialogues - form interaction
4	Not designed keeping physician users in mind	Overall Objective is Business not Medicine	Structuring system requirements - Process
5	Unnecessary pop-ups: avoid designing any legitimate information in a manner that resembles advertising (e.g., banners, animations, pop-ups)	Specialty Specific System Requirements	Structuring system requirements - Process
6	hard stops	Specialty Specific System Requirements	Structuring system requirements - Process
7	Not designed keeping medical management of patient in mind	Overall Objective is Business not Medicine	Structuring system requirements - Process
8	No end date for the acute conditions rolling over in patient history	Unorganized data	Data Modeling
9	Inconsistencies in the medical history impact inpatient treatment plans	Unorganized data	Data Modeling
10	Absence of real-time/on the spot incident reporting/hyperlinks that connect immediately	Vendor Support	Automated Support - Realtime feedback
11	Poor search function - to find hyperlinks that pulls in patient info from chart to note	Functional deficiencies	Functionality
12	Updates erase the hyperlinks created by physicians	Functional deficiencies	Updates impacting old/existing data
13	Poor search function-Unlabeled documents/notes using hie features	Functional deficiencies	Functionality
14	Inability of the EHR to automatically connect to and update patient's insurance formulary	Interoperability	Interoperability
15	Multiple dropdown options for one diagnosis	Unorganized data	View integration
16	Takes long from login screen to getting to a chart	EHR Inefficiency	System speed
17	Templates-Building notes takes time; 2-4 hours at the end of the day or outside of regular work hours	EHR Inefficiency	Customization
18	Poor search function-nomenclature of the medications/tests is not standardized	Functional deficiencies	Functionality
19	Grouping tests that can be ordered together can save physicians time	Specialty Specific System Requirements	Structuring system requirements - Process
20	Points of care that go together are not grouped together on the EHR interface	Specialty Specific System Requirements	Structuring system requirements - Process

21	Inability of the EHR to automatically connect to and update patient's insurance formulary	Functional deficiencies	Structuring system requirements - Data Entry Fields - Entry, Units
22	Unrealistic unit of measurement for medication ordering. User has to do the calculations	Specialty Specific System Requirements	Structuring system requirements - Data Entry Fields - Entry, Units
23	Remove unnecessary pop-ups e.g. sepsis pop-ups; Keep necessary pop-ups e.g. drug interactions	Specialty Specific System Requirements	Structuring system requirements - Process
24	Does not represent the specialty specific workflow	Specialty Specific System Requirements	Structuring system requirements - Process
25	Lack of interoperability	Interoperability	Interoperability
26	Too much unstructured data that does not present a full clinical picture quickly	Unorganized data	Structuring system requirements - Process
27	Need for specialty specific customizable templates and views	Specialty Specific System Requirements	Customization
28	System upgrades that moves icons on UI without any increased functionality	EHR Inefficiency	Unnecessary upgrades
29	Too many clicks	EHR Inefficiency	Menu Interaction
30	Autofill Information - required but at some place autofill can increase the risk of error as well	Functional deficiencies	Data Modeling
31	Cluttered screen takes up cognitive energy until muscle memory takes over	Unorganized data	Menu Interaction and form interaction
32	External IT support can be time-taking	Vendor Support	System Support
33	Federal requirements of quality measures are not built into the system and workarounds using templates and really hard	Functional deficiencies	Functionality
34	hard stops don't fit practice	Specialty Specific System Requirements	Structuring system requirements - Process
35	Modularity – multiple usernames and passwords and going back and forth between systems to take care of just one patient	Interoperability	Functionality
36	Hardware and connectivity issues that slows down the workflow	Hardware and Connectivity	Structuring system requirements
37	When Patient words cannot be translated into a button	Technical Inability	Functionality
38	Going back and forth multiple screens to reconcile information and then wait for pages to load	EHR Inefficiency	View integration
39	Process of reconciling medications from other providers is complex and the EHR system is not designed smart enough to handle the care coordination between levels of care delivery	Functional deficiencies	Functionality
40	All the needed information should be on one or two screens without having to toggle between screens and systems. Just simplify.	EHR Inefficiency	View integration
41	EHR doesn't replicate how a physician would the interview	EHR Inefficiency	Structuring system requirements - Process
42	Sub-specialties need a specialized EHR system, generic adult EHR won't work	Specialty Specific System Requirements	Structuring system requirements - Process
43	For EMR to function at its best it has to be personalized for practitioners	Specialty Specific System Requirements	Structuring system requirements - Process

44	Go back to the paper chart and turn that electronic such that physician experience is a solid one	Specialty Specific System Requirements	Structuring system requirements - Process
45	Multiple steps to order medication	EHR Inefficiency	View integration
46	Even the specialized chemo software is not very user friendly and very hard to customize.	Specialty Specific System Requirements	Structuring system requirements - Process
47	Any change in the dates of the chemo administering plan throws off the treatment schedule and system is not designed to handle such deviations from normal	Specialty Specific System Requirements	Structuring system requirements - Process
48	IOT in healthcare – EHR interfacing with ICU monitoring, ventilators and other devices. Physicians can customize what and how they want to look at and be able to remove the extra clutter.	Interoperability	Functionality
49	EMR can be designed better to highlight new growth/ cultures and improve the readability of the microbiology tab	User Interface	UI/UX
50	Due to COVID more data is amassing into an EMR but it is not organized	Unorganized data	Data Modeling
51	Uses of free texts instead of checkboxes to improve the readability of the notes.	User Interface	UI/UX

APPENDIX R: Clinicians Task Time Data Collection Format

	Source→	Sinsky et al. Ann of Int Med 2016	Overhage and Johnson Pediatrics 2020	Hilliard et al. JAMIA 2020	Hilliard et al. JAMIA 2020	Adler-Milstein et al. JAMIA 2020
	Clinician Type→	Ambulatory (PCP+ Specialists)	PCP	PCP	Non-PCP	PCP
Workflow Processes ↓	Clinician Task-Type ↓					
-Enter Current Meds -Complete Past Medical History -Clinician Assessment -Document Procedure/Enter Vitals	Time with Patient (in secs/encounter)	93				
-Clinician Log-in -Clinician Log-out	Time with NonPatient (in secs/encounter)	45				
Follow-up record	EHR-DocReview (in secs/encounter)	69	661	130	123.75	
Document test results	EHR-TestResult (in secs/encounter)	59	17			
	EHR-MedOrder (in secs/encounter)	59	112			
Order tests	EHR-OtherOrder (in secs/encounter)	52	104			

	Admin Insurance (in secs/encounter)	49				
Complete ADT pathway	Admin Scheduling (in secs/encounter)	59				
	OtherObservation (in secs/encounter)	524				
	OtherAggregate (in secs/encounter)	183				
	Other Transit (in secs/encounter)	15				
	OtherPersonal (in secs/encounter)	109				
	EHRTime AfterHours on Scheduled Days (in mins/day)					23.14
	EHRTime on Unscheduled Days (in mins/day)					225.5

VITA

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