10-26-2015

Informing the Design and Deployment of Health Information Technology to Improve Care Coordination

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Informing the Design and Deployment of Health Information Technology to Improve Care Coordination

by

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A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
Department of Industrial and Management Systems Engineering
College of Engineering
University of South Florida

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Date of Approval:
October 20, 2015

Keywords: Hospital Readmission, Health Information Exchange, Healthcare Systems Engineering

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Abstract

In the United States, the health care sector is 20 years behind in the use of information technology to improve the process of health care delivery as compared to other sectors. Patients have to deliver their data over and over again to every health professional they see. Most health care facilities act as data repositories with limited capabilities of data analysis or data exchange. A remaining challenge is, *how do we encourage the use of IT in the health care sector that will improve care coordination, save lives, make patients more involved in decision-making, and save money for the American people?* According to Healthy People 2020, several challenges such as making health IT more usable, helping users to adapt to the new uses of health IT, and monitoring the impact of health IT on health care quality, safety, and efficiency, will require multidisciplinary models, new data systems, and abundant research. In this dissertation, I developed and used systems engineering methods to understand the role of new health IT in improving the coordination, safety, and efficiency of health care delivery.

It is well known that care coordination issues may result in preventable hospital readmissions. In this dissertation, I identified the status of the care coordination and hospital readmission issues in the United States, and the potential areas where systems engineering would make significant contributions (see Appendix B). This literature review introduced me to a second study (see Appendix C), in which I identified specific patient cohorts, within chronically ill patients, that are at a higher risk of being readmitted within 30 days. Important to note is that the largest volume of preventable hospital readmissions occurs among chronically ill patients. This study was a retrospective data analysis of a representative patient cohort from Tampa, Florida, based on multivariate logistic regression and Cox proportional hazards models. After finishing these two

studies, I directed my research efforts to understand and generate evidence on the role of new health IT (i.e., health information exchange, HIE) in improving care coordination, and thereby reducing the chances of a patient to be unnecessarily readmitted to the hospital.

HIE is the electronic exchange of patient data among different stakeholders in the health care industry. The exchange of patient data is achieved, for example, by connecting electronic medical records systems between unaffiliated health care providers. It is expected that HIE will allow physicians, nurses, pharmacists, other health care providers and patients to appropriately access and securely share a patient's vital medical information electronically, and thereby improving the speed, quality, safety and cost of patient care. The federal government, through the 2009 Health Information Technology for Economic and Clinical Health (HITECH) Act, is actively stimulating health care providers to engage in HIE, so that they can freely exchange patient information. Although these networks of information exchange are the promise of a less fragmented and more efficient health care system, there are only a few functional and financially sustainable HIEs across the United States. Current evidence suggests four barriers for HIE:

- Usability and interface issues of HIE systems
- Privacy and security concerns of patient data
- Lack of sustainable business models for HIE organizations
- Loss of strategic advantage of "owning" patient information by joining HIE to freely share data

To contribute in reducing usability and interface issues of HIE systems, I performed a user needs assessment for the internal medicine department of Tampa General Hospital in Tampa, Florida. I used qualitative research tools (see Appendix D) and machine learning techniques (see Appendix E) to answer the following fundamental questions: How do clinicians integrate patient information allocated in outside health care facilities? What are the types of information needed the most for efficient and effective medical decision-making? Additionally, I built a strategic gaming model (see Appendix F) to analyze the strategic role of "owning" patient information that health care providers lose by joining an HIE. Using bilevel mathematical programs, I mimic the hospital decision of joining HIE and the patient decision of switching from one hospital to another one. The fundamental questions I tried to answer were: What is the role of competition in the decision of whether or not hospitals will engage in HIE? Our mathematical framework can also be used by policy makers to answer the following question: What are the optimal levels of monetary incentives that will spur HIE engagement in a specific region? Answering these fundamental questions will support both the development of user-friendly HIE systems and the creation of more effective health IT policy to promote and generate HIE engagement.

Through the development of these five studies, I demonstrated how systems engineering tools can be used by policy makers and health care providers to make health IT more useful, and to monitor and support the impact of health IT on health care quality, safety, and efficiency.

Chapter 1: Introduction

The elderly constitute 13.7% of the population in the United States, and they consume 42% of the hospital expenditures. In addition, during FY 2006, it was found that 72% of Medicare hospitalizations were treated in teaching hospitals, many of whom are critically ill patients in need of advanced care. Unfortunately, care coordination among health care providers during patient treatment is not optimal. Gaps in communication during health care delivery can cause unnecessary hospital readmissions and serious breakdowns in care. These gaps in communication have been recognized as the leading root cause of sentinel events by The Joint Commission between 1995 and 2006. To put this into context, patient hand off during hospital transfers represent a critical situation where inaccessible clinical information delays understanding of patient's health condition, and consequently hinders his/her timely treatment. Having timely access to a patient's medical history should improve the delivery of care during a patient hand off. Health information exchange (HIE) has emerged as a mechanism to foster care coordination and reduce communication gaps. Although the 2009 HITECH Act has directed substantial funding to promote HIE, recent studies have reported low engagement across hospitals and other health care providers in the United States. This engagement is particularly low for large academic tertiary care institutions in competitive markets. Several authors claim that better designed HIE systems would stimulate HIE engagement.

The objective of this dissertation is to inform the design and deployment of health IT aiming at improving care coordination and reducing hospital readmissions. The rationale underlying this investigation is that, once the health professionals information needs during treatment of hospitalized patients are understood, better HIE systems will be designed, representing an opportunity to improve the adoption and utilization of HIE across the United States.

1.1 Research Contributions

The research contributions of the studies presented in Appendices B, C, D, E, and F are described next.

1. In the first study (see Appendix B), I synthesized published evidence on the status of the hospital readmission problem in the United States, as well as identifying research gaps where systems engineering can make a significant impact.

2. In a following study (see Appendix C), I identified risk factors associated with 30-day preventable hospital readmission for congestive heart failure, acute myocardial infarction, pneumonia, and diabetes patients. Important to note is that the largest proportion of hospital readmissions is among chronically ill patients.

3. Since improving care coordination is key to reducing hospital readmissions, I directed my efforts towards analyzing the role of new health IT (i.e., health information exchange, HIE) in improving care coordination. The study introduced in Appendix D revealed physicians' preferences, habits, and barriers to collect and use patient information allocated in electronic medical records of other health care facilities. This study is the first user needs assessment previous HIE implementation in a teaching hospital.

4. In the study introduced in Appendix E, I measured physicians' actual information-gathering habits in electronic medical records of other health care facilities. This study innovates by explicitly incorporating the health care providers' needs and voice in what data/information an HIE must deliver.

5. Although HIE has the potential of supporting care coordination efforts, there are still few functional HIE networks in the United States. One of the barriers for hospitals to engage in HIE is the potential loss of competitive advantage by freely sharing patient data with other competing hospitals. In the work presented in Appendix F, I generated a deeper understanding of the role of competition in the decision of whether or not a hospital will join an HIE network.

6. Finally, I designed and built a mathematical framework to find the optimal levels of federal monetary incentives that will spur HIE adoption in a given region (see Appendix F). Many modeling studies about HIE adoption have already been undertaken. A crucial difference among these studies is the type of interaction that is assumed among competing hospitals. In more competitive models, the type of interaction can often be summarized in terms of the hospital's conjectural variation, in which each hospital has about the way its competitors may react if it varies its decision to join HIE. The models presented in Appendix F make the following contribution. Unlike previous approaches, they calculate an oligopolistic equilibrium of HIE adoption in a given region using the hospital utility function conjectural variations, while considering the discrete range patient's decision of where to receive (or purchase) health care. I argue this is a more realistic representation of the HIE market. The resulting optimization problem for each hospital is a bi-level mathematical program.

In summary, the work presented in this dissertation provide guidelines, anchored in systems engineering methods, to developers to better design HIE systems, to health IT policy makers to find optimal levels of monetary incentives that will spur HIE engagement, and to researchers as to where significant contributions can be made to contribute in the care coordination and hospital readmission problems. These contributions will be significant because design guidelines based on providers' needs should result in HIE systems with a higher degree of personalization, facilitating use and adoption, and therefore improved care coordination and health care delivery. It is expected to have an impact in the creation of better HIE systems, as well as the development of further longitudinal studies that will provide stronger evidence-based guidelines.

Chapter 2: A Literature Review of Preventable Hospital Readmissions

Preventable readmissions are a large and growing concern throughout healthcare in the United States, representing as many as 20% of all hospitalizations (30-day post-discharge) and an estimated $17 to $26 billion in unnecessary costs annually. National quality initiatives and Medicare reimbursement financial incentives have stimulated significant efforts by healthcare organizations to reduce readmissions via a number of approaches and interventions. Given the severity and complexity of this problem, this paper summarizes the recent literature describing descriptive and predictive readmission studies as well as proposed interventions. A total of 112 publications were identified and grouped into three general categories: descriptive analyses, intervention studies, and predictive analyses. While a significant amount of work has been conducted in each of these areas, very few industrial engineering or operation research studies focused directly on readmissions have been reported in the literature. This paper, therefore, concludes with a discussion of potential areas in which industrial engineers might make meaningful contributions to this important problem. The complete manuscript *A Literature Review of Preventable Hospital Readmissions*, under review in IIE Transactions on Healthcare Systems Engineering, can be found in the Appendix B.

Chapter 3: Preventable Readmission Risk Factors for Patients with Chronic Conditions

Evidence indicates that the largest volume of hospital readmissions occurs among patients with preexisting chronic conditions. Identifying these patients can improve the way hospital care is delivered and prioritize the allocation of interventions. In this retrospective study, we identify factors associated with readmission within 30 days based on claims and administrative data of nine hospitals from 2005 to 2012. We present a data inclusion and exclusion criteria to identify potentially preventable readmissions. Multivariate logistic regression models and a Cox proportional hazards extension are used to estimate the readmission risk for 4 chronic conditions (congestive heart failure [CHF], chronic obstructive pulmonary disease [COPD], acute myocardial infarction, and type 2 diabetes) and pneumonia, known to be related to high readmission rates. Accumulated number of admissions and discharge disposition were identified to be significant factors across most disease groups. Larger odds of readmission were associated with higher severity index for CHF and COPD patients. Different chronic conditions are associated with different patient and case severity factors, suggesting that further studies in readmission should consider studying conditions separately. The article *Preventable Readmission Risk Factors for Patients with Chronic Conditions*, published in the Journal for Healthcare Quality, can be found in the Appendix C.

Chapter 4: A User Needs Assessment to Inform Health Information Exchange Design and Implementation

Important barriers for widespread use of health information exchange (HIE) are usability and interface issues. However, most HIEs are implemented without performing a needs assessment with the end users, healthcare providers. We performed a user needs assessment for the process of obtaining clinical information from other health care organizations about a hospitalized patient and identified the types of information most valued for medical decision-making. Quantitative and qualitative analysis were used to evaluate the process to obtain and use outside clinical information (OI) using semi-structured interviews (16 internists), direct observation (750 h), and operational data from the electronic medical records (30,461 hospitalizations) of an internal medicine department in a public, teaching hospital in Tampa, Florida. 13.7% of hospitalizations generate at least one request for OI. On average, the process comprised 13 steps, 6 decisions points, and 4 different participants. Physicians estimate that the average time to receive OI is 18 h. Physicians perceived that OI received is not useful 33âĂŞ66% of the time because information received is irrelevant or not timely. Technical barriers to OI use included poor accessibility and ineffective information visualization. Common problems with the process were receiving extraneous notes and the need to re-request the information. Drivers for OI use were to trend lab or imaging abnormalities, understand medical history of critically ill or hospital-to-hospital transferred patients, and assess previous echocardiograms and bacterial cultures. About 85% of the physicians believe HIE would have a positive effect on improving healthcare delivery. Although hospitalists are challenged by a complex process to obtain OI, they recognize the value of specific information for enhancing medical decision-making. HIE systems are likely to have increased utilization and effectiveness if specific patient-level clinical information is delivered at the right time to the right users. The article *A User Needs Assessment to Inform Health Information Exchange Design and Implementation*, published in BMC Medical Informatics and Decision Making, can be found in the Appendix D.

Chapter 5: Uncovering Hospitalists' Information Needs From Outside Healthcare Facilities in the Context of Health Information Exchange Using Association Rule Learning

Important barriers to health information exchange (HIE) adoption are clinical workflow disruptions and troubles with the system interface. Prior research suggests that HIE interfaces providing faster access to useful information may stimulate use and reduce barriers for adoption; however, little is known about informational needs of hospitalists. Our objective was to study the association between patient health problems and the type of information requested from outside healthcare providers by hospitalists of a tertiary care hospital. We searched operational data associated with fax-based exchange of patient information (previous HIE implementation) between hospitalists of an internal medicine department in a large urban tertiary care hospital in Florida, and any other affiliated and unaffiliated healthcare provider. All hospitalizations from October 2011 to March 2014 were included in the search. Strong association rules between health problems and types of information requested during each hospitalization were discovered using Apriori algorithm, which were then validated by a team of hospitalists of the same department. Our results indicate that only 13.7% (2,089 out of 15,230) of the hospitalizations generated at least one request of patient information to other providers. The transactional data showed 20 strong association rules between specific health problems and types of information exist. Among the 20 rules, for example, abdominal pain, chest pain, and anaemia patients are highly likely to have medical records and outside imaging results requested. Other health conditions, prone to have records requested, were lower urinary tract infection and back pain patients. The presented list of strong co-occurrence of health problems and types of information requested by hospitalists from outside healthcare providers not only informs the implementation and design of HIE, but also helps to target future research on the impact of having access to outside information for specific patient cohorts. Our data-driven approach helps to reduce the typical biases of qualitative research. The complete manuscript *Uncovering Hospitalists' Information Needs From Outside Healthcare Facilities in the Context of Health Information Exchange Using Association Rule Learning*, under review in Applied Clinical Informatics, can be found in the Appendix E.

Chapter 6: A Strategic Gaming Model for Health Information Exchange Markets

Here we describe a strategic gaming model for estimating willingness of healthcare organizations to adopt HIE, and to demonstrate its use in HIE policy design. We formulated the model as a bi-level integer mathematical program. Multi-hospital mixed strategy Nash equilibrium is searched using a quasi-Newton method, and are interpreted as the hospitals' willingness to adopt HIE based on its competitors decisions. We applied our model to 1,093,177 encounters over a 7.5-year period in 9 hospitals located within three adjacent counties in Florida. For this community and under a particular set of assumptions, proposed federal penalties of up to $2,000,000 have a higher impact on increasing HIE adoption than current federal monetary incentives. Medium-sized hospitals are more reticent to HIE than large-sized hospitals. In the presence of a 4-hospital collusion to not adopt HIE, neither federal incentives nor proposed penalties increase hospitals' willingness to adopt HIE. Hospitals may set HIE adoption decisions to threaten the value of interconnectivity even with federal incentives in place. Competition among hospitals, coupled with volume-based payment systems, creates no incentives for smaller hospitals to exchange data with competitors. Medium-sized hospitals need targeted actions to mitigate market incentives to not adopt HIE. Strategic gaming modeling clarified HIE adoption decisions and market conditions at play in an extremely complex technology implementation, which may inform other communities trying to achieve EMR interconnectivity and the development of new and stronger HIE policy. The complete manuscript *A Strategic Gaming Model for Health Information Exchange Markets*, under review in the Journal of the American Medical Informatics Association, which is under review in the Journal of the American Medical Informatics Association can be found in the Appendix F.

Chapter 7: Conclusion

This dissertation has answered, to some extent, the five questions we began with:

- Question 1: What is the current status of the hospital readmission problem in the United States?

  Answer: Hospital readmissions are a large and growing concern representing as many as 20% of all hospitalizations, with an estimated annual cost of $17 billion. During the last 10 years, most of the published evidence has concentrated on data analysis to identify those at a higher risk of readmission and assessment of interventions aiming at reducing such risk. Only a few large-scale unified studies have been conducted. Moreover, the scope of most studies is either disease specific (limited to one disease), fairly localized (limited to a single hospital) or too broad (limited to nationwide hospitalizations with no clinical information).

- Question 2: What are the conditions that make a patient more likely to be readmitted?

  Answer: For chronically ill patients, the more days the patient stays in the hospital, the higher the likelihood of being readmitted within 30 days. Particularly for a patient with heart failure, having behavioral health issues is associated to a higher likelihood of being readmitted. In terms of payer class, it was found that patients with Medicaid and Medicare have a higher risk of being readmitted as compared to commercial insurance. Finally, those admitted though the emergency department are at a higher risk of being readmitted.

- Question 3: How do clinicians integrate patient information allocated in outside health care facilities to improve medical-decision making and care coordination?

Answer: In an urban tertiary care hospital, although hospitalists are challenged by a complex process to integrate patient information allocated in outside health care facilities, they recognize the value of specific data types. It was found that, on average, the process to obtain patient records comprises 13 steps, 6 decision points, 4 different participants, and lasts 18 hours. Most of the time, physicians find that the patient information received is irrelevant or late. Common problems with the process are receiving extraneous notes and the need to re-request information. Common situations where obtain patient records is key are trending lab results abnormalities, understanding medical history of critically ill patients or hospital-to-hospital transferred patients, and assessing previous electrocardiograms and bacterial cultures. About 85% of the hospitalists believe HIE will have a positive effect on improving health care delivery.

- Question 4: What are the types of information needed the most for efficient and effective medical decision-making?

  Answer: In the internal medicine department of a urban tertiary care hospital, outside medical records are commonly request for abdominal pain and anemia patients. For abdominal pain patients, for example, medical records are usually requested to find previous MRIs, CTs and endoscopies.

- Question 5: What is the role of competition in the decision of whether or not hospitals will engage in HIE?

  Answer: Our simulation experiments indicate that the higher the competition among hospitals in a given region, the higher incentives/penalties are needed for HIE engagement. It was also found that penalties, instead of incentives, would have a stronger impact on generating collaboration via HIE engagement.

This dissertation has advanced the current understanding of the hospital readmission problem. Through a literature review, it has discussed definitions, measurements, and descriptive analyses reported in the literature, as well as the many interventions utilized by health care providers to reduce patient readmission risk. It has also identified and discussed the current research gaps that could be addressed by systems engineers. For instance, several opportunities exist to conduct predictive analytics to identify those patients at a high risk of readmission. Also, the development of new health information technology to support care coordination efforts, such as HIE, may have a key role in reducing hospital readmission. Through statistical modeling, this dissertation has identified risk factors for preventable hospital readmission. The list of risk factors may be useful to other investigators who are trying to predict whether or not a patient will be readmitted. Also, recognizing those patients cohorts at high risk of readmission, may help health care providers to target their interventions.

This dissertation has also advanced the current understanding of HIE, and its role in supporting care coordination and medical decision-making. Through qualitative methods, it has more deeply described the clinicians' expectations and values regarding HIE, as reflected in individual internists' usage of a fax-based HIE system. The simple framework of drivers and barriers may be useful to other investigators who are trying to understand users needs in the context of HIE design and implementation.

Trough quantitative methods, it has documented internists information requests patterns in the context of HIE. Outcomes of this investigation will help HIE developers and implementers recognize commonly requested clinical information by the patient chief complaint, and thereby prioritize information display. This knowledge could be used to inform the design of new technical functionalities beyond simple data exchange. For instance, electronic decision support systems that identify, retrieve and present, at the point of care, patient clinical data allocated in information systems from other health care providers.

Through mathematical models, it has generated a deeper understanding of the role of competition in the HIE participation decision, which may help modify current policies and incentives structures, which seek to foster HIE participation and thereby collaboration among competitors.

With the increasing evidence supporting the effect of HIE use on reduced utilization and costs in emergency departments, there is the need of stronger policies and incentives to convince competing organizations to share patient data electronically.

Further research is needed to predict hospital readmission. Data accumulating from widespread use of electronic medical records (EMR) and HIE networks provide an underexploited opportunity to perform individualized patient care using data-driven approaches. A hospital readmission may be influenced by numerous factors including physiologic indices of case severity, treatment strategies, and socioeconomic factors. Accordingly, developing predictive models for readmissions requires hypothesis-driven selection of predictors, robust sample sizes, and the use of computational methods that may exploit these large datasets. Supervised machine learning methods may be used to leverage heterogeneous (structured and unstructured) demographic, physiologic, laboratory and imaging data to improve early identification of patients at high risk for HF readmission.

Future research is also needed to determine the effect of clinician access to information from HIE networks. Linking HIE to patient outcomes is important to demonstrate its value and to promote HIE engagement. To develop clinical decision support systems that are fed by HIE data, more research needs to be done to understand clinician-user and the system in which the users and the technology interact. Improved knowledge of different kinds of care transitions (e.g., hospital transfers) would be essential to understand the value of HIE. Such knowledge could also be used to inform the design of new technical functionalities beyond simple data exchange. HIE will evolve to support richer forms of collaboration among health care stakeholders including health care providers, patients, health IT vendor companies, public health specialists, federal policy experts, and the HIE organizations that supply data exchange services.

Health information technology, in the form of HIE, presents enormous opportunities for improving care coordination and for other secondary uses, especially related to quality analysis and population/personalized health care analytics, which may be essential to achieve sustainability in

HIE organizations and improvements in health care delivery. After many years of failed attempts to have an interconnected health care system, HIE may be on a path toward success, now that the federal government and other important stakeholders are engaged and have invested considerable resources. However, it may still take many years and experiments before HIE realizes its potential. It will be important to learn from the successes and failures, and to continue employing systems engineering tools to understand and improve HIE.

Appendices

Appendix A: Copyright Permissions for Manuscripts Presented in Appendices B, C, D, E and F

Appendix A includes the copyright approvals for the material presented in this dissertation.

Appendix A (continued)

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Diego Martinez <dmartinezcea@mail.usf.edu>

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1 message

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Kind regards
Birgit

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From: Diego Martinez

To: Jess Holzer

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Appendix A (continued)

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> >
> > **Title**: Uncovering hospitalists' information needs from outside healthcare facilities in the context of health information exchange using association rule learning
> > **Short Title**: Hospitalist information needs and HIE
> > **Authors**: Diego A. Martinez, Elia Mora, Martino Gemmani, José Zayas-Castro
> > **Topic**: eHealth Systems
> > **Submission type**: Research Article
> > **Manuscript ID**: ACI-2015-06-RA-0068.R1
> >
> > Thank you in advance.
> >
> > Best regards,
> > Diego
> >
> > --

Appendix A (continued)

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Journal: BMC Medical Informatics and Decision Making

Manuscript ID: 4130412391654976

Thank you in advance.

Best regards,
Diego

Appendix A (continued)

Institute of Industrial Engineers
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August 25, 2015

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Appendix A (continued)

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Appendix B: A Literature Review of Preventable Hospital Readmissions

Appendix B shows the manuscript titled, "A Literature Review of Preventable Hospital Readmissions", which is under review in IIE Transactions on Healthcare Systems Engineering.

Appendix B (continued)

A Literature Review of Preventable Hospital Readmissions

Hong Wan, Lingsong Zhang, Steven Witz, Kenneth J. Musselman, Fang Yi, Cody J. Mullen, James Benneyan, Jose L. Zayas-Castro, Diego A. Martinez, Florentino Rico, Laila N. Cure

Preprint Submitted to IIE Transactions on Healthcare Systems Engineering

Abstract

Preventable readmissions are a large and growing concern throughout healthcare in the United States, representing as many as 20% of all hospitalizations (30-day post-discharge) and an estimated $17 to $26 billion in unnecessary costs annually. National quality initiatives and Medicare reimbursement financial incentives have stimulated significant efforts by healthcare organizations to reduce readmissions via a number of approaches and interventions. Given the severity and complexity of this problem, this paper summarizes the recent literature describing descriptive and predictive readmission studies as well as proposed interventions. A total of 112 publications were identified and grouped into three general categories: descriptive analyses, intervention studies, and predictive analyses. While a significant amount of work has been conducted in each of these areas, very few industrial engineering or operation research studies focused directly on readmissions have been reported in the literature. This paper, therefore, concludes with a discussion of potential areas in which industrial engineers might make meaningful contributions to this important problem.

Appendix B (continued)

Keywords: Readmissions, re-hospitalizations, bounce backs, discharge process

1. Background

Hospital readmissions and their associated costs have become an increasing concern over the last several years (Boutwell, 2011), with provisions of the 2010 Patient Protection and Affordable Care Act establishing penalties for hospitals with higher than average avoidable readmission rates (Santamour, 2011). These penalties are an attempt to curb the rising number of readmissions and their associated costs, which are significant. The Agency for Healthcare Research and Quality reported that in 2011 there were approximately 3.3 million adults, all-cause, 30-day readmissions in the United States at an estimated cost of $41.3 billion (Hines, Barrett, Jiang, & Steiner, 2014). The cost of readmissions for Medicare patients alone stands at an estimated $26 billion annually, out of which $17 billion are potentially preventable (Goodman, Fisher, Chang, Raymond, & Bronner, 2013; Robert Wood Johnson Foundation, 2013).

While the problem is compelling, its underlying causes are difficult to analyze. Readmission studies are often hampered by a lack of information on follow-up data among different care sites and the cohort of hospitals used in the studies (public vs. private hospitals, Medicare vs. Non-Medicare patients). For example, Chen et al. (2010) estimated a hospital cost model per medical condition, and used the observed mean cost of care per case for Medicare patients and a predicted mean cost of care to compare hospitals in a certain location and with specific characteristics. This study is limited by the current inability of tracking patients going to different hospitals.

Examples of common initial ("index") diagnoses for hospitalizations and subsequent readmissions include congestive heart failure (CHF), renal failure, urinary tract infection (UTI), pneumonia, and chronic obstructive pulmonary disease (COPD) (Ouslander, Diaz, Hain, & Tappen, 2011; Press et al., 2010), with common causes including incomplete care during a hospital stay (Benbassat & Taragin, 2000; Ornstein, Smith, Foer, Lopez-Cantor, & Soriano, 2011), exacerbation of the initial condition or complication of the initial treatment (Marcantonio et al., 1999), substandard care during the transition out of the hospital (Boutwell, 2011), adverse drug events post discharge (Allaudeen, Vidyarthi, Maselli, & Auerbach, 2010), and poor compliance to medication, exercise, and diet instructions after patients are discharged (Krumholz et al., 2002).

Estimates of the percent of discharged adult patients readmitted within a month of their original hospitalization range from 5% to 29% (Thomas & Holloway, 1991), with 90% of these readmissions estimated as unplanned (Jencks, Williams, & Coleman, 2009). For Medicare fee-for-service beneficiaries discharged between July 2005 and June 2008, the median 30-day readmission rates were 19.9% for acute myocardial infarction (AMI) and 24.4% for heart failure (HF) (Krumholz, Merrill, & Schone, 2009), with the overall annual cost of unplanned re-hospitalizations estimated at $17.4 billion in 2004 (Jencks et al., 2009). According to hospital discharge data for residents of New York, Pennsylvania, Tennessee, and Wisconsin, from January to July in 1999, hospital costs for preventable readmissions were roughly $730 million (Friedman & Basu, 2004). Readmitted patients also tend to have significantly poorer outcomes and longer lengths of stay. More broadly, readmissions often are proposed as a general marker for the quality of care received during an index admission (Weissman et al., 1999). For example, early unplanned readmissions of patients with heart failure, diabetes, and obstructive lung disease have been linked to the quality of care during their previous hospital stay (Ashton, Kuykendall, Johnson, Wray, & Wu, 1995).

Despite this evidence and ensuing efforts to reduce readmissions, Karen E. Joynt and Jha (2012) found that risk-adjusted 30-day readmission rates for congestive heart failure, pneumonia and acute myocardial infarction between 2002 and 2009 showed little improvement, arguing that overall 30-day readmission rates for these conditions may not appropriately reflect the quality of care because causes for most of those readmissions may not be under the hospital's control. The Dartmouth Atlas Project in collaboration with the Robert Wood Johnson Foundation (2013) reported that overall improvement in 30-day readmission rates between 2008 and 2010 has been "slow and inconsistent" throughout academic hospitals in the United States.

The report points out that focusing on 30-day readmission rates may not improve the health of patients because it may lead to neglecting other important aspects of care, such as the prevention of longer term readmissions for patients with chronic diseases and the increase in hospital mortality (Goodman et al., 2013; Robert Wood Johnson Foundation, 2013). Still, 30-day readmission rates continue to be the metric used to evaluate the performance of hospitals.

The Centers for Medicare and Medicaid Services (CMS) began reporting 30-day risk-standardized readmission rates as a measure of hospital quality in 2009. In 2012, they introduced a reimbursement system that penalizes hospitals with a high rate of readmissions for pneumonia, congestive heart failure, or acute myocardial infarction (AMI) patients. The penalty is assessed across all Medicare reimbursements for services rendered in a given hospital.

Given the magnitude of the readmission problem, financial pressures, and considerable national focus within healthcare, this manuscript summarizes recent literature describing the general problem, analytical studies, and intervention approaches. The intent is to provide sufficient background to enable systems engineers and related researchers to contribute meaningfully applied and theoretical work to this important area. Where useful, representative studies are cited to provide context and additional insight, although the intent is not to exhaustively review all papers.

A total of 112 papers from 1987 through 2011 were generated by a keyword search within PubMED and reviewed for their key contributions. As summarized in Figure 1, the number of papers in each category increased significantly in the past few years, somewhat coinciding with the 2009 introduction of Medicare's new reimbursement policy. Partly driven by these reporting and financial motivations, institutions and researchers have developed a variety of strategies to identify and reduce preventable readmissions. Some studies have focused on describing the readmissions landscape at the national level while others have focused on the local and hospital levels. There have been a number of predictive studies exploring risk factors for different patient groups to better understand the dynamics of readmissions. These studies have shown a

Appendix B (continued)

pervasive lack of standard systems or processes to ensure post-discharge compliance to exercise treatment instructions (e.g. medication, diet, and follow-up care) (Krumholz et al., 2002), so a number of the studies have focused on developing interventions to improve information transfer and other aspects of the discharge process. We grouped the papers into three categories: descriptive analysis (43), intervention studies (34), and statistical or predictive models (35).

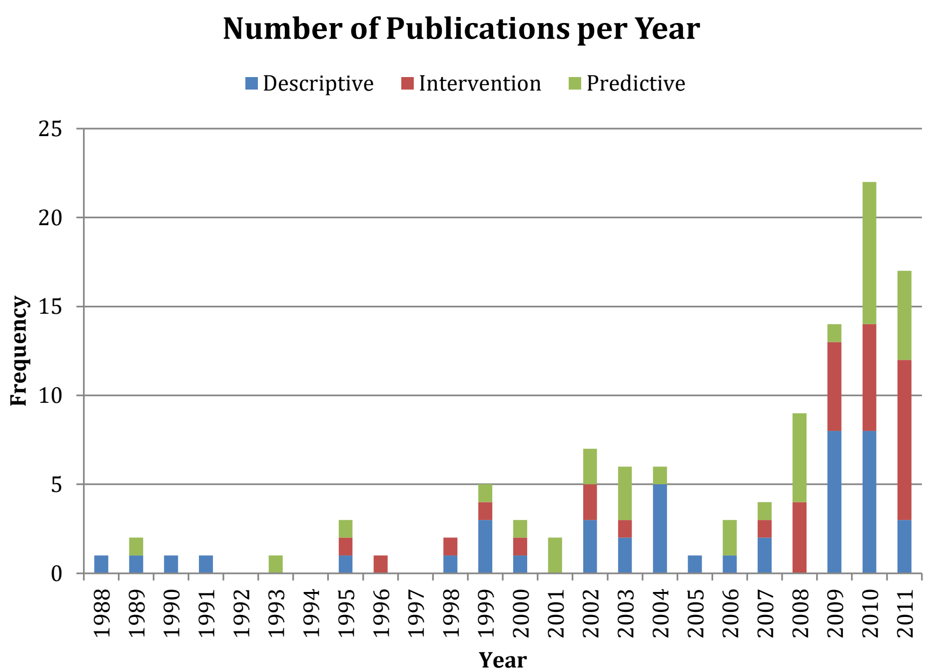

Figure 1. Publications categorized as descriptive, intervention, or predictive.

The remainder of this paper is organized as follows: Section 2 discusses definitions, measurements, and descriptive analyses reported in the literature; Section 3 summarizes common preventive approaches proposed, evaluated or practiced by healthcare institutions; and Section 4 reviews statistical and predictive models discussed in the literature. A discussion of research gaps and opportunities for future work is presented in Section 5, the last section of this paper.

2. Definitions, Measurements, and Descriptive Analyses

Depending on the study or context, hospital readmissions are typically defined using a time window from the time of discharge, i.e. "*n*-day readmission" (common windows being 14, 30, 90, and 180-day readmission rates). A study by Heggestad and Lilleeng (2003) found 28% of all readmissions occur within 10 days, 49% within 30 days, and 79% within 90 days. Estimating exact readmission rates, however, is problematic due to a variety of data accuracy and patient tracking issues. For example, the primary and secondary diagnoses of readmitted patients often are not the same as their index admissions, even when the cases are linked. Moreover, same-hospital readmissions capture only 80.9% of all-hospital readmissions, with a significant number of patients being readmitted to a different hospital (Nasir et al., 2010).

Figure 2 illustrates the general context within which readmissions occur. After the initial (index) admission and treatment, a patient is usually released home following a discharge process in which home care, diet, medication, exercise, and other instructions are reviewed with the patient and his or her family. Depending on the patient's condition and the particular healthcare organization, in the time between this initial discharge and subsequent readmission, the patient may be contacted by phone to review discharge instructions and address any questions, be visited by a home health nurse or other provider, or be monitored by some form of home monitoring technology. Later, the patient may be readmitted to a hospital under the same or different diagnostic coding. For example, a patient could be readmitted for a broken leg when his or her index admission was the result of heart failure. Adding to the complexity, the patient may return for care, but not to the same hospital. For example, in examining Medicare patients readmitted within 30 days after undergoing one of three common surgical procedures, Gonzalez, Shih, Dimick, and Ghaferi (2013) found that only 64% were readmitted to the same hospital. Finally, reasons for a readmission can vary. They include, but are not limited to, non-compliance

Appendix B (continued)

to discharge instructions, the quality or completeness of care received during the initial hospital stay, and an iatrogenic injury. This care cycle for the patient may occur several times between a discharge location, such as the patient’s home, and a hospital or set of hospitals.

Many factors can come into play when investigating readmissions. For instance, if in the above example the patient’s admission due to a broken leg to the same hospital is counted as a readmission, it may cause misleading conclusions about the quality of care that patient received during his or her index admission for heart failure. Moreover, readmissions analyses often do not consider readmissions to another hospital due to lack of data, whereas these readmissions may be an indicator of unsatisfactory patient care at the index admission hospital. Also, the time between readmissions may be reflective of the quality of hospital care or post-discharge care. For example, short cycling may be due to the patient’s poor adherence to discharge instructions and have nothing to do with the quality of care provided by the hospital.

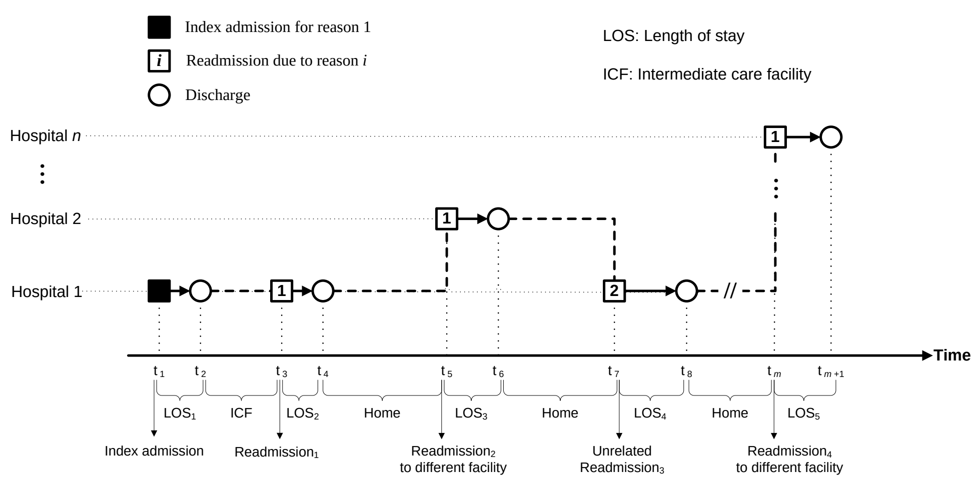

Figure 2. General readmissions context

Readmissions can also be classified as planned or unplanned, where planned refers to an intentional admission that is a scheduled part of a patient’s care plan, such as chemotherapy or rehabilitation. One study estimated 47.1% of patients readmitted within 30 days were unplanned (Maurer & Ballmer, 2004). Unplanned readmissions can be either (potentially) preventable (e.g., congestive heart failure, bacterial pneumonia, urinary tract infection, surgical wound infection) or non-preventable (e.g., trauma, unexpected finding of malignancy). While estimates vary for the percent of unplanned admissions that are preventable, Jiang, Russo, and Barrett (2009) reports, in a study of nearly 4.4 million admissions in 2006, that 18% of the adult admissions were potentially preventable. Ascertaining whether a patient's condition is preventable or not can exacerbate the accurate identification of a readmission. In practice, making this determination is often assessed by various types of clinical experts (e.g. surgeons, general physicians) whose background may influence their analyses and conclusions.

Preventable readmission rates range widely in the literature from 5.5% to 49.3% (see Table 1 in Appendix), due to practice-to-practice variations, different diagnoses, and a lack of consistent definition and measurement criteria (Clarke, 1990). Some authors agree that the use of readmission rates as an indicator of the quality of care in a previous admission may not always be reasonable (Benbassat & Taragin, 2000; Chen et al., 2010; Weissman et al., 1999). Therefore, factors beyond those solely related to quality of care during a hospital stay should be considered as potential causes of readmissions.

3. Prevention Interventions

Most of the intervention articles reviewed culled recommendations from the literature or experimental studies. Summaries of many of these interventions can be found in Greenwald, Denham, and Jack (2007); Kanaan (2009); Olson et al. (2011); Simmons (2010) and Taylor (2010). Osei-Anto, Joshi, Audet, Berman, and Jencks (2010) and Jweinat (2010) summarize successful interventions and provide a framework for the development of readmission prevention programs in hospitals. Two of the papers Trisolini, Aggarwal, Leung, Pope, and Kautter (2008) and Healthleaders Media (2010) focus on healthcare quality.

Table 2 in the appendix summarizes common interventions discussed in the literature. A large majority of these publications tend to focus on a few diagnoses or a specific population of patients. Table 3 shows the patient diagnoses most commonly cited, including congestive heart failure (CHF) and acute myocardial infarction (AMI). High-risk patients were often determined using some form of assessment (Bisognano & Boutwell, 2009; Rayner, Temple, Marshall, & Clarke, 2002).

Most of the interventions can be grouped into general improvements for transitions of care, redesigning the discharge process, or enhanced follow-up care strategies. Interventions to improve transitions of care included: (1) enhanced assessment of patient needs (such as quality of inpatient care, accurate medication reconciliation, effective education and communication at discharge, post-discharge support, follow-up referrals, effective communication of clinical prognosis, and proactive end-of-life care planning) (Bisognano & Boutwell, 2009; Institute for Healthcare Improvement, 2009b); (2) general guidelines for readmission prevention efforts (such as assessing, prioritizing, implementation and monitoring) (Osei-Anto et al., 2010), and (3) models for improved care coordination/transition between settings (Bodenheimer, 2008; Institute for Healthcare Improvement, 2010b).

The main components in interventions focusing on the discharge process consisted of: (1) the careful design of the discharge process and all related activities (Clancy, 2009; Institute for Healthcare Improvement, 2009a); (2) the use of patient-centered approaches (Jack et al., 2008; Jweinat, 2010); (3) the simplification of the discharge process for patients and caregivers (Balaban, Weissman, Samuel, & Woolhandler, 2008); (4) providing patients with clear instruction on risks, symptoms, complications, and their adequate management (Grafft et al., 2010; Patient Safety Authority, 2005); and (5) the use or development of information technology for the communication of key discharge information (Motamedi et al., 2011). Better education of patients and medical staff was also found to decrease readmission rates (Bisognano & Boutwell, 2009).

Common interventions directed towards post-discharge, follow-up care included the following: (1) increased frequency or intensity of follow-up activities (Rayner et al., 2002; Rich et al., 1995); (2) increased primary care access (Cline, Israelsson, Willenheimer, Broms, & Erhardt, 1998; Strunin, Stone, & Jack, 2007; Weinberger, Oddone, & Henderson, 1996); (3) high-risk screening tools to determine the need for intervention (Manning, 2011); (4) home health monitoring technology (Institute for Healthcare Improvement, 2010a); (5) improved communication between primary care and inpatient providers to facilitate timely and accurate transfer of key patient information (Ornstein et al., 2011); (6) healthcare worker (e.g., physician, nurse, physiotherapists) visits after discharge (Andersen et al., 2000; Ornstein et al., 2011); and (7) phone-based follow-up after discharge (Harrison, Hara, Pope, Young, & Rula, 2011; Kasper et al., 2002) or a combination of visits and phone calls after discharge (Naylor et al., 1999).

Performance metrics used to evaluate the effectiveness of interventions include compliance rates, readmission rates, days until readmission, readmission lengths of stay, readmission costs, emergency department visit costs, overall cost of care, mortality rates, inpatient/outpatient resource utilizations, patient satisfaction, and quality of life. Compliance rates attempt to measure the extent to which an intervention is being carried out (e.g., rates of follow-up and counts of incomplete outpatient workups (Balaban et al., 2008). Two articles proposed measures to better evaluate readmissions (Bhalla & Kalkut, 2010; Institute for Healthcare Improvement, 2003). However, there is still a need to define and implement standardized performance metrics that can assist in assessing or validating the level of success of an intervention. Studies should incorporate a measure of the fidelity of the actual intervention implementation as a predictor variable for the performance metrics being evaluated. The development of these metrics should reflect the priorities of patients and healthcare providers, and should facilitate the identification of specific areas in need for reengineering.

Even though most studies developed their proposed interventions based on widely accepted good clinical practices and patient-centered care, three studies did not find significant differences between intervention and control groups (Grafft et al., 2010; Rayner et al., 2002; Weinberger et al., 1996). One study found that the efficacy of their intervention was relatively smaller in congestive heart failure patients as compared to other patients (Naylor et al., 1999), which may suggest the need to tailor interventions according to the needs of different patient groups. A recent report from the Agency for Healthcare Research and Quality on the effectiveness of interventions to improve transitions for acute stroke and myocardial infarction patients found that while some outcomes, such as hospital length of stay and mortality, are often improved by intervention, most studies have not been able to clearly demonstrate a positive or negative effect on metrics of systems' or patient's outcomes (Olson et al., 2011). Five studies included a cost analysis based on costs per patient, annual healthcare cost per patient, total Medicare reimbursements for health services at 24 weeks after discharge, discharge costs, and possible implications of readmission cost policies on care quality (Balaban et al., 2008; Cline et al., 1998; Naylor et al., 1999; Rich et al., 1995; Simmons, 2010). Cost benefit analysis of interventions are especially important in the light of the Medicare reimbursement penalty for those hospitals with consistently increased readmission rates.

The actual adoption of intervention strategies to reduce readmission rates in hospitals is questionable (Butler & Kalogeropoulos, 2012). Bradley et al. (2012) found that although most hospitals in the hospital-to-home (H-2-H) quality improvement initiative had a written objective related to reducing preventable readmissions for patients with heart failure or AMI, actual interventions and levels of implementation varied widely. The survey study found that less than 50% of the hospitals surveyed had fully implemented any single key practice and less than 3% were currently using all of the 10 practices investigated in the study. The practices with the highest adoption level included: partnering with community hospitals (49.3%), partnering with local hospitals to manage high risk patients (23.5%), linking inpatient and outpatient prescription records (28.9%), and consistently sending the discharge summary to the patient's primary medical doctor (25.5%). Regardless of the intervention strategies selected, the implementation of such strategies needs to be carefully planned and executed to maximize their potential for success.

Measuring the success of an intervention is still a challenge because of the difficulty of defining variables that capture the quality of healthcare delivery, patient satisfaction, health status, and healthcare provider satisfaction. Consequently, some interesting challenges may exist when conducting statistical and predictive analysis of both intervening factors and outcome variables, which is discussed in the next section.

4. Statistical and Predictive Analysis

The most common statistical approaches used in analyzing readmission data are logistic regression and survival analysis (Almagro et al., 2006; Beck, Khambalia, Parkin, Raina, & Macarthur, 2006; Epstein, Tsaras, Amoateng-Adjepong, Greiner, & Manthous, 2009; French, Bass, Bradham, Campbell, & Rubenstein, 2008; Greenblatt et al., 2010; Hannan et al., 2003; Hasan et al., 2010; Hendryx et al., 2003; Holloway & Thomas, 1989; Jasti, Mortensen, Obrosky, Kapoor, & Fine, 2008; Luthi, Burnand, McClellan, Pitts, & Flanders, 2004; Mudge et al., 2010; Neupane, Walter, Krueger, Marrie, & Loeb, 2010; Philbin & DiSalvo, 1999; Tsuchihashi et al., 2001; van Walraven et al., 2010; Weiss, Yakusheva, & Bobay, 2010). Other more sophisticated statistical models have also been applied in specific situations. For example, Medress and Fleshner (2007) used Wilcoxon nonparametric and Fisher's exact tests to compare continuous and categorical variables, respectively. Allaudeen et al. (2010) employed multivariable generalized estimating equations for clustering of patients within physician assignments and calculating the adjusted odds ratios to identify factors significantly associated with readmissions. Generally speaking, standard statistical tests and criteria are typically used to identify associated factors (e.g. t-test, chi-square test, Pearson correlations); and more sophisticated techniques are used for prediction models. For example, Glasgow, Vaughn-Sarrazin, and Kaboli (2010) used t-tests to analyze continuous variables and chi-square tests to analyze categorical variables to compare patient baseline characteristics between two groups (those discharged against medical advice and those with a standard discharge), multivariable Cox proportional hazard models to predict the time to readmission, and stepwise model selection to "determine which of the remaining covariates also represented significant risk factors in each separate model."

The work to identify factors associated with readmissions is summarized in Table 4 in the Appendix. We can see that a fair amount of work has been published studying factors associated with readmissions in specific patient populations. Heart failure and pneumonia are by far the most commonly studied diseases. The factors considered include patients' biological, social, and economical characteristics and hospital discharge and post-discharge processes. It should be noted that several research articles have demonstrated that education (Koelling, Johnson, Cody, & Aaronson, 2005; Krumholz et al., 2002), intervention (Hernandez et al., 2010; Riegel et al., 2002), and hospital discharge programs (Jack et al., 2009; Lappe et al., 2004) have had positive effects on readmissions.

Another important body of literature has to do with constructing statistical models to predict readmission rates. Table 7 in the appendix summarizes papers from 1989 through 2010 related to readmission prediction; and Table 8 summarizes the focus of each paper and the frequency of the common predictive factors. Age and gender were the two most common predictive factors analyzed, and have appeared in roughly two-thirds of all examined papers. Comorbidity, length of stay, prior admissions, and ethnicity were also commonly identified predictors. Other studies focused on very specific predictive factors, especially those that considered a subset of patients, with specific diagnoses or diseases sometimes tested as independent or causal variables. In a study of psychiatric patients, for instance, Hendryx et al. (2003) examined the association between a primary diagnosis of schizophrenia and subsequent readmission.

While some authors examined all types of admissions and readmissions, it is more common to limit the patient sample to a diagnosis or demographic subset. For instance, Lagoe, Noetscher, and Murphy (2001) and Luthi et al. (2004) both focused on patients diagnosed with heart failure, since this is the leading diagnosis associated with readmission.

Generally speaking, the data sources used in these predictive studies can be classified into one of two levels:

(1) Hospital, in which data are typically collected and analyzed within one to three specific healthcare facilities. An example is the study reported by Hendryx et al. (2003) at the Harborview Medical Center in Seattle, WA.

(2) Database, in which data are typically collected and analyzed at the state or national level. Examples include studies reported by Hannan et al. (2003); Holloway and Thomas (1989); Philbin and DiSalvo (1999), and Lagoe et al. (2001) conducted in New York State hospitals.

Tables 5 and 6 in the appendix summarize these hospital and database studies, respectively. The latter type of study generally had larger sample sizes because of their wider service regions. A focus on heart failure patients is even more common in database studies, as seen in Hofer and Hayward (1995); Keenan, Normand, and Lin (2008); Krumholz et al. (2000); Luthi et al. (2003); and Philbin and DiSalvo (1999). In addition, two studies used hospitals rather than patients as the unit of analyses. In one, Boulding, Glickman, Manary, Schulman, and Staelin (2011) investigated the relationship between patient satisfaction survey results aggregated at the hospital level and 30-day hospital readmission rates. In the other, Hansen, Williams, and Singer (2011) explored the relationship between 30-day risk-adjusted readmission rates and patient safety climates, assessed through employee surveys.

5. Challenges and Opportunities for Industrial Engineers

As shown in the literature review, we have witnessed a growing analysis of various aspects related to hospital readmissions. During the last decade much of the work has concentrated on data analysis and the design and assessment of interventions. A fair amount of consulting and proprietary methods are also increasingly appearing in hospitals and conferences. The IE/STAT/OR community has become more and more involved in the area, and we are presented with several promising opportunities.

Appendix B (continued)

While the analysis methods used tend to be fairly rigorous, few large-scale unified studies have been conducted. The scope of most studies are either disease specific, fairly localized (i.e. limited to a single hospital) or very broad (i.e. statewide admissions). Opportunities exist in the IE/STAT/OR research domain to develop models that better capture the necessary granularity that can be integrated in a more generalizable manner. This will require proposing and validating new readmission metrics, especially as they relate to all-cause, comorbid and longitudinal (i.e., over 30 days) conditions. Research into readmission patterns that extend beyond the ubiquitous frequency measures may also prove to be helpful. Additionally, the need for care coordination and population health studies abound. Out of this should come new methodologies that better incorporate the human experiences.

Several opportunities exist to contribute to the analysis and improvement of readmissions. One of the most common limitations throughout the various studies was the availability of data to identify, manage and prevent readmissions. In the case of intervention implementation and evaluation, the most common barriers included a lack of uniform data about factors that may be related to readmissions (Harrison et al., 2011), difficulty in sharing information across organizations, assessing and ensuring patient and provider compliance (Grafft et al., 2010; Patient Safety Authority, 2005), and a lack of validated processes for determining if the readmissions were related or not to an index admission (Andersen et al., 2000; Institute for Healthcare Improvement, 2010b).

Evaluating the risk of (preventable) readmissions is a challenge due to the lack of clinical data in the identification of significant factors. Clinical data is available; however, physician notes, test results, and images are not structured and are not easily extracted for statistical analyses. Moreover, the existence of confounding factors can limit data analysis, a problem not easily overcome for observational studies (Hernandez et al., 2010). For example, Moore, Wisnivesky, Williams, and McGinn (2003) retrospectively analyzed medical errors related to care discontinuity between inpatient and outpatient settings, although patients with work-up errors may be subsequently managed differently than others. Weissman et al. (1999) studied care quality during initial admissions, but did not consider post-discharge care, while van Walraven, Seth, Austin, and Laupacis (2002) analyzed the effect of discharge summary availability, but did not control for care during the initial hospitalization.

The classification of readmissions (e.g., planned versus unplanned, avoidable versus unavoidable) can also limit analyses, especially those mainly focused on a specific type of readmission. For example, Jencks et al. (2009) focused on related adverse readmissions (RAR) and non-RARs, classifying readmissions as planned or unplanned and avoidable or unavoidable. Classification errors can also occur due to the lack of a second independent examiner to confirm (Maurer & Ballmer, 2004), potentially introducing noise into subsequent statistical analyses. Some studies do not distinguish between planned and unplanned readmissions (Dormann et al., 2004; Nasir et al., 2010). Again, this is often due to a lack of data. A standardized system for classifying readmission types, therefore, would make results more generalizable and cross-comparable, especially to facilitate selection of appropriate intervention strategies or predictive models.

As in most health services research, clinical information systems or administrative data are used predominantly in retrospective studies, which can limit the types of available data and reduce the ability to conduct meaningful analyses. The effects of potentially important factors, consequently, are likely to be underestimated (Elixhauser, Steiner, Harris, & Coffey, 1998; Harrison et al., 2011; Marcantonio et al., 1999) and incomplete data can restrict the generalization of results. There are opportunities for improvement at all levels of data procurement, including data collection, data selection, population selection, definition of guidelines to classify events and patients, and identification of confounding factors. The current effort, however, to develop data exchange standards and information systems for tracking patients across institutions should enable better implementation and research opportunities. Some of this research might include geospatial and socio-demographic analysis of healthcare seeking behaviors to better understand where, how often, and why patients seek the care they do. This understanding could lead to adopting strategies for better coordinated, patient-centered care.

Other limitations in many of the published studies also include the short time spans of sampled data (Miles & Lowe, 1999) and the use of nonrandomized or observational comparisons (Lappe et al., 2004) or narrow sample groups (Ashton et al., 1995; Koelling et al., 2005; Krumholz et al., 2009). For example, Ashton et al. (1995) studied the association between the quality of inpatient care and early readmission only among males using Veterans Affairs hospitals, potentially limiting the generalizability of the results.

In terms of study populations, many papers focused on particular disease types, age groups, or social statuses. In the case of studies related to interventions, addressing specific patient populations has shown significant benefits since these efforts can focus more effectively on the particular needs of these patient groups (Grafft et al., 2010).

Regarding the use of interventions, implementation-specific factors and intervention characteristics were not explicitly addressed in a majority of the studies. For example, most interventions are formed by a set of activities or strategies that may or may not work as a whole (e.g., assessment methodology and follow-up procedure variables, such as time to follow-up or type of follow-up). The majority of studies focused on validating the overall effectiveness of the proposed intervention, but few attempted to find the specific characteristics of the population or the particular activities and strategies that made the intervention successful (Naylor et al., 1999). For example, an intervention to reduce readmissions of patients with heart failure discharged to skilled nursing facilities found that enhanced communication among caregivers was key to reducing the corresponding preventable readmissions (Jacobs, 2011). It is important to distinguish between strategies that are effective for the general population and strategies that are effective for specific patient groups, so that risk assessment can be used to determine the "optimal intervention plan" needed, if any.

Appendix B (continued)

Although many studies identified factors associated with readmissions, most did not draw conclusions about causality nor offer guidelines on how to optimize any particular intervention to reduce readmission rates (Balaban et al., 2008; Bell et al., 2009; Chen et al., 2010; Krumholz et al., 2002; van Walraven & Bell, 2002). For example, van Walraven and Bell (2002) found that readmission risk may decrease with better discharge summary availability during post-discharge visits, but was unable to determine how dissemination of discharge summaries to follow-up physicians might avoid readmissions.

From an industrial engineering perspective, several opportunities exist to contribute to the above efforts and issues. Perhaps most obvious are opportunities to conduct various types of statistical modeling, potentially including data mining of large unstructured data sets and novel predictive modeling methods beyond those already being used. Additionally, data reduction methods such as feature recognition and principal components analysis, pseudo experimental design methods to test causality, and modern visual exploration data analysis methods could have particular value. Research more aligned with operations research might include deterministic and probabilistic intervention optimization, stochastic patient flow and transition models, comparative and cost effectiveness models for interventions, and agent-based or game theoretic models.

Despite the heightened focus on preventing readmissions, it is not always clear if, where, and why readmission rates are improving. Ross et al. (2010), for example, found no reduction in readmission rates nor significant differences in rates among hospitals from 2004 through 2006 for Medicare beneficiaries discharged after hospitalization for heart failure. Thus, development and use of methods to better estimate readmission rates and causality would seem useful as well. Similarly, performance measures to evaluate intervention strategies (e.g., compliance, frequency, coverage) are needed to monitor their effectiveness. Given the complexities, human interactions, and interdependencies of multiple factors, exploring various socio-technical analyses that better address the human factor seem especially appropriate. System dynamics models also might be useful here, possibly including analysis of various financial and public reporting incentives and of the introduction and optimal design of accountable care organizations and other new integrated delivery system concepts.

In summary, numerous opportunities exist for industrial engineering and operations research methods to complement, support, and extend the hospital readmissions work done to date, which is now mostly being conducted within other disciplines. Given the importance of this problem across the entire United States healthcare system, it is appropriate for industrial engineers to begin to apply their expertise to this challenging area.

Appendix B (continued)

Appendix

Table 1: Proportion of preventable readmissions among unplanned readmissions

Study	Group	Design[1]	Number patients	Time interval, day	Number of Readmissions / Rates	Preventable readmissions, % of all readmissions
Clarke (1990)	General medical and geriatric Surgical	R	207 166 60 48	0-6 21-27 0-6 21-27	(in total 100 random case notes) (74 were available) 25 case notes (18 available) 25 case notes (19 available) 25 case notes (19 available) 25 case notes (18 available)	31.5 6.3 (Total: 16.5) 49.3 19.0 (Total: 34.6)
Miles and Lowe (1999)	All RA data from JHH[2] in Oct. 1998 by ACHS[3] indicator	R	3,081 admissions	28	437 readmissions with adequate data involving 371 patients	5.5 (out of the 437 readmissions)
Maurer and Ballmer (2004)	DIM[4] of KSW[5]	P	884 IA[6]	30 90	12.3% 19.5% (planned & unplanned)	9.4 18.5 (out of unplanned)
Friedman and Basu (2004)	Persons with initial PQI[7] admission	R	345,651	3 mo 6 mo	- 35.3%	13.3% 19.4% (out of the PQI admissions)

[1] R: retrospective, P: prospective, [2] JHH: John Hunter Hospital, [3]ACHS: Australian Council on Healthcare Standards, [4] DIM: Department of Internal Medicine, [5] KSW: Kantonsspital Winterthur, [6] IA: index admissions, [7] PQI: Prevention Quality Indicator

Appendix B (continued)

Table 2: Summary of common interventions discussed in the literature

Intervention type	Intervention	References
Discharge planning	Disease and treatment education	(Balaban et al., 2008; Bickmore, Pfeifer, & Jack, 2009; Bisognano & Boutwell, 2009; Cline et al., 1998; Institute for Healthcare Improvement, 2009a, 2009b, 2010a; Jack et al., 2008; Manning, 2011; Naylor et al., 1999; Ornstein et al., 2011; Patient Safety Authority, 2005; Rich et al., 1995; Weinberger et al., 1996)
	Review of medication	(Bisognano & Boutwell, 2009; Cline et al., 1998; Fleming & Haney, 2013; Institute for Healthcare Improvement, 2009a, 2010a; Kasper et al., 2002; Osei-Anto et al., 2010; Rich et al., 1995; Weinberger et al., 1996)
	Prescribed diet	(Rich et al., 1995)
	Assignment of PCP	(Osei-Anto et al., 2010; Weinberger et al., 1996)
	Self-management education	(Cline et al., 1998; Coleman, Parry, Chalmers, & Min, 2006; Fleming & Haney, 2013; Institute for Healthcare Improvement, 2009a, 2010a; Jack et al., 2008; Manning, 2011; Osei-Anto et al., 2010; Patient Safety Authority, 2005)
	Identify sources of error/risk at discharge	(Anthony et al., 2005; Institute for Healthcare Improvement, 2009b)
	Risk screen patients	(Institute for Healthcare Improvement, 2010b; Manning, 2011; Osei-Anto et al., 2010)
	Interdisciplinary/multi-disciplinary clinical team	(Osei-Anto et al., 2010)
Transitions of care	Computer-enabled discharge communication	(Motamedi et al., 2011)
	Effective patient and family engagement	(Institute for Healthcare Improvement, 2010a, 2010b)
	Coordination among care sites	(Bisognano & Boutwell, 2009; Bodenheimer, 2008; Coleman et al., 2006; Fleming & Haney, 2013; Institute for Healthcare Improvement, 2009a, 2009b, 2010a, 2010b; Jacobs, 2011; Manning, 2011; Motamedi et al., 2011; Ornstein et al., 2011; Osei-Anto et al., 2010; Press et al., 2010)
	Assignment of a care transitions coordinator / transitions coach	(Coleman et al., 2006; Fleming & Haney, 2013)
Follow-up	Home visits	(Andersen et al., 2000; Naylor et al., 1999; Osei-Anto et al., 2010; Rich et al., 1995)

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	Telephone contact	(Balaban et al., 2008; Bisognano & Boutwell, 2009; Cline et al., 1998; Harrison et al., 2011; Institute for Healthcare Improvement, 2009a; Jacobs, 2011; Kasper et al., 2002; Naylor et al., 1999; Osei-Anto et al., 2010; Rich et al., 1995; Weinberger et al., 1996)
	Compliance with instructions given at hospital	(Harrison et al., 2011; Jacobs, 2011; Motamedi et al., 2011; Rich et al., 1995; Weinberger et al., 1996)
	Primary care clinic follow-up appointment	(Coleman et al., 2006; Grafft et al., 2010; Institute for Healthcare Improvement, 2009b, 2010a; Jordan et al., 2012; Kasper et al., 2002; Osei-Anto et al., 2010; Rayner et al., 2002; Weinberger et al., 1996)
	Access to nurse consultation (short notice)	(Cline et al., 1998; Naylor et al., 1999)
	Medical rehabilitation/therapy after discharge	(Jordan et al., 2012; Mudrick et al., 2013)

Appendix B (continued)

Table 3: Common diagnoses mentioned in the intervention literature.

Patient Group	References
CHF	(Bisognano & Boutwell, 2009; Cline et al., 1998; Coleman et al., 2006; Institute for Healthcare Improvement, 2010a, 2010b; Kasper et al., 2002; Manning, 2011; Rich et al., 1995; Weinberger et al., 1996)
Diabetes	(Coleman et al., 2006; Weinberger et al., 1996)
COPD	(Coleman et al., 2006; Weinberger et al., 1996)
AMI	(Andersen et al., 2000; Coleman et al., 2006; Institute for Healthcare Improvement, 2010a; Mudrick et al., 2013)
Ambulatory surgery	(Patient Safety Authority, 2005)
General	(Balaban et al., 2008; Bickmore et al., 2009; Bodenheimer, 2008; Grafft et al., 2010; Harrison et al., 2011; Institute for Healthcare Improvement, 2009a, 2009b, 2010b; Jack et al., 2008; Jacobs, 2011; Jweinat, 2010; Motamedi et al., 2011; Ornstein et al., 2011; Osei-Anto et al., 2010; Press et al., 2010; Rayner et al., 2002)
Other	(Coleman et al., 2006; Jordan et al., 2012)

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Table 4: Factors associated with readmissions

Study	Factor	Sample Group, N=sample size	Results
Elixhauser et al. (1998)	Comorbidity	Non-maternal inpatients from in 438 acute care hospitals California N=1,779,167	Comorbidities were associated with longer length of stay, higher hospital charges, and mortality and had different effects among different patient groups
van Walraven et al. (2002)	Discharge summary availability	Patients discharged for acute medical illness from Ottawa Civic Hospital with OHIP[1] number N=888	A decreased trend in readmissions was found when the factor was added (relative risk, 0.74)
Krumholz et al. (2002)	Education and support	Patients in YNHH[2]with heart failure from Oct. 1997 to Sep.1998, age≥=50 N=88	Intervention group had a significantly lower risk of readmission (hazard ratio, 0.56)
Riegel et al. (2002)	nurse case-management telephone intervention	Patients with heart failure from 2 southern California hospitals N=358	The heart failure hospitalization rate was 45.7% and 47.8% lower in the intervention group at 3 and 6 months
Moore et al. (2003)	Medical errors related to discontinuity care from inpatient to outpatient setting	General patients who had been hospitalized at a large academic medical center N=86	49% of patients experienced at least 1 medical error and patients with work-up error were 6.2 times more likely to be re-hospitalized within 3 months
Dormann et al. (2004)	Adverse drug reactions	General patients from internal medicine of UHEN[3]; N=1000 admissions	ADRs were not significant with readmissions but with LOS
Lappe et al. (2004)	Hospital-based discharge medication program (DMP)	Cardiovascular disease from the 10 largest hospitals in UIHS[4]: Pre-DMP(1996-1998): N=26000; DMP (1999-2002): N=31465	Reduced relative risk for death and readmissions (hazard ratios, 0.81, 0.92)
Ather, Chung, Gregory, and Demissie (2004)	Insurance provider	Adults with asthma from NJDHHS[5]; N=15864	Significant increased risk of 7-day readmission for managed care patients compared to indemnity (OR, 1.67) and LOS is also significant for readmissions
(Koelling et al., 2005)	One-hour discharge education	Patients with chronic heart failure from University of Michigan Hospital; N=223; Control group=116	Patients receiving the education intervention had lower risk of re-hospitalization (relative risk, 0.65)
(Vira, Colquhoun, &	Medication reconciliation	Generally from a Canadian community hospital; N=60	18% of patients were detected having clinical important unintended variance after

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Etchells, 2006)			reconciliation
(Kartha et al., 2007)	Depression	Adults inpatient with at least 1 hospital admissions in the past 6 month; N=144	Depression tripled the odds of re-hospitalization (odds ratio, 3.3)
(Bailey et al., 2009)	Risks of severity	Indigenous and non-indigenous children of bronchiolitis from Royal Darwin Hospital, age≤2; N=101	No significant difference for readmission rates among the 2 groups, but indigenous children had more Severe illness
(Jha, Orav, & Epstein, 2009)	Public reporting of discharge planning	Congestive Heart Failure, using HQA[6] database	NO large reduction in unnecessary readmissions
(Jack et al., 2009)	A reengineered hospital discharge program	Adults patients admitted to medical teaching service of Boston Medical Center; N=749	The intervention group(N=370) had a lower rate of hospital utilization (0.314 vs 0.451 visit per person per month)
(Hernandez et al., 2010)	Early physician follow-up	Patients ≥65 with heart failure from 225 hospitals; N=30316	Patients who are discharged from hospitals that have higher early follow-up rates have a lower risk of 30-day readmission
(Boulding et al., 2011)	Patient satisfaction	430,982 patients with acute myocardial infarction (AMI) 1,02 9,578 patients with heart failure 912,522 patients with pneumonia	Higher overall satisfaction and satisfaction with discharge planning are associated with lower 30-day risk-standardized readmission rates
(Hansen et al., 2011)	Hospital patients safety climate	36,375 employees in 67 hospitals	There is positive association between lower safety climate and higher readmission rates for AMI and HF
(K. E. Joynt, Orav, & Jha, 2011)	Race and site of care (non-minority and minority)	Medicare beneficiaries (3.1 million in 2006 - 2008)	Black patients were more likely to be readmitted after hospitalization for AMI, congestive HF and pneumonia
(Onukwugha et al., 2011)	Discharges against medical advice(AMA)	348,572 patients from nonfederal acute care hospitals in Maryland with CVD (Cardiovascular disease)	The percentage of patients who were readmitted was higher among AMA group versus non-AMA group

[1]OHIP: Ontario Health Insurance Plan, [2]YNHH: Yale New Haven Hospital, [3]UHEN: University Hospital Erlangen-Nuremberg, [4]UIHS: Utah-based Intermountain Health Care System, [5]NJDHHS: New Jersey Department of Health and Senior Services, [6]HQA: Hospital Quality Alliance Program

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Table 5: Summary of hospital-level studies

Paper	Location/Type	Sample Size	Notes
(Allaudeen et al., 2010)	550-bed tertiary care academic medical center in San Francisco, CA	6805 patients 10,359 admissions	General medicine
(Almagro et al., 2006)	Acute-care teaching referral center in Barcelona, Spain.	129 patients	COPD
(Capelastegui et al., 2009)	400-bed teaching hospital in the Basque country (northern Spain)	1117 patients	Pneumonia
(Halfon et al., 2002)	Centre Hospitalier Universitaire Vaudois, Lausanne, Switzerland (CHUV) - 800-bed university hospital	3474 patients	
(Hendryx et al., 2003)	Harborview Medical Center in Seattle, WA	1384 patients	Psychiatric
(Jasti et al., 2008)	7 hospitals in Pittsburg	577 patients	CAP
(Lagoe et al., 2001)	3 hospitals in Syracuse, New York: Community-General Hospital-306 beds; Crouse Hospital-566 beds; St. Joseph's Hospital Health Center-431 beds	1500+ discharges	CHF
(Luthi et al., 2004)	3 Swiss academic medical centers (all urban public university hospitals)	934 patients	HF
(Medress & Fleshner, 2007)	Cedars-Sinai Medical Center in Los Angeles, CA	202 patients	Colitis
(Mudge et al., 2010)	Internal Medicine Department of a tertiary teaching hospital in Brisbane, Australia.	142 patients	
(Weiss et al., 2010)	4 Midwestern hospitals	162 patients	Medical-surgical

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Table 6:Summary of database-level studies

Paper	Location/Type	Sample Size	Notes
(Beck et al., 2006)	Canadian Institute for Health Information database	334,959	Pediatric patients
(Boult et al., 1993)	Longitudinal Study of Aging (LSOA)	5,876	Elderly people 70 years old and older
(French et al., 2008)	National Medicare and Veterans Health Administration (VHA) facilities.	41,331	Medicare Elderly veterans
(Glasgow et al., 2010)	129 acute care Veterans Administration hospitals	32,819 patients 1,930,947 admissions	Left against medical advice veterans
(Greenblatt et al., 2010)	Centers for Medicaid and Medicare Services	42,348 patients	Colectomy
(Goldfield et al., 2008)	249 Florida inpatient hospitals	4,311,653 admissions	
(Hannan et al., 2003)	New York State hospitals	16,325 patients	CABG surgery
(Hasan et al., 2010)	Multi Center Hospitalist Study data (designed in six academic medical centers in the US)	10,946 patients	General medicine
(Hofer & Hayward, 1995)	190 hospitals in the statewide Michigan Inpatient Database	603,959 patients	HF, gastrointestinal, neuologic, pulmonary disease
(Holloway & Thomas, 1989)	1980 National Medical Care Utilization and Expenditure Survey data	2206 patients	
(Keenan et al., 2008)	2002-2005 Medicare claims data frfom the Medicare Enrollment Database	>1 million admissions	HF
(Krumholz et al., 2000)	18 Connecticut Hospitals	2176 patients	HF 65+
(Luthi et al., 2003))	50 community hospitals in Colorado, Connecticut, Georgia, Oklahoma, and Virginia	2943 patients	HF
(Onukwugha et al., 2011)	Maryland Health Services Cost Review Commission Database	348,572 patients	CVD
(Philbin & DiSalvo, 1999)	New York State Department of Health	42,731 patients	CHF

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(van Walraven & Bell, 2002)	11 hospitals (6 university-affiliated, 5 community) in Ontario	4812 patients	Medical or surgical
(van Walraven et al., 2010)	Discharge Abstract Database (DAD), which records all discharges from Ontario hospitals	2.4 million patients	Non-elective admissions adult

Table 7: Summary of papers from 1989 through 2010 related to readmission prediction

Author	Dates	R /P	Readmission Definition	Diagnosis	Sample group	Readmission Rate	Method	Significant Factors
(Allaudeen et al., 2010)	Jun 2006 May 2008	R	30-days unplanned	General medicine patients	Sample size: 6805; The University of California , San Francisco Medical Center	17.0%	Multivariable generalized estimating equations	Black race, Medicaid as payer, High risk medications, Comorbidities (CHF, renal disease, cancer, weight loss, iron deficiency anemia)
(Allaudeen, Schnipper, Orav, Wachter, & Vidyarthi, 2011)	Mar 2008 Apr 2008	R	30-days	general medicine patients	Sample size: 164; University of California , San Francisco Medical Center	32.7%	Receiver-operating characteristic (ROC) curves	Older age, male sex, poor self-rated general health, availability of an informal caregiver, coronary artery disease, diabetes, hospital admission within last year, more than six doctor visits during the previous year
(Almagro et al., 2006)	Oct 1996 May 1997	P	1-year	COPD	Sample size: 129; Acute care teaching referral center, Barcelona, Spain	58.1%	Multivariable logistic regression	Previous hospitalization for, COPD, Hypercapnia at discharge, Poorer quality of life

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(Beck et al., 2006)	Jan 1996 Dec 2000	R	30-days	Pediatric	Sample size: 334,959; Pediatric population (Age≤18) Canadian Institute for Health Information Discharge Abstract Database	3.4% 3.6% (discharged on Friday) 3.3% (discharged on Wednesday)	Multivariable logistic regression	Number of diagnoses; In-hospital complications; Hospital admission within prior 6 months
(Berman et al., 2011)	2008	R	30-days	Advanced liver disease	Sample size: 447; Hepatology service at Indiana University Hospital and University of Colorado Hospital	20%	Multivariate analyses	End-stage liver disease scores; presence of diabetes; male gender
(Boulding et al., 2011)	July 2005 June 2008	R	30-day risk standardized	AMI, HF, Pneumonia	Unit of analysis was hospital; AMI: 1798 hospitals, HF: 2561 hospitals, Pneumonia: 2562 hospitals. Hospital Compare database by the US Department of Health and Human Services; HCAHPS patient satisfaction survey data	20% (for all clinical areas)	Logistic regression	Overall patient satisfaction for AMI, HF, pneumonia (negatively); Patient satisfaction with discharge planning for HF (negatively)

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(Boult et al., 1993)	1984	R	4-year	Elderly people	Sample size: 5876; 70 years old and older; Longitudinal Study of Aging (LSOA) data	28.4%	Multivariate logistic regression	Age, Gender, Self-rated general health, Availability of an informal caregiver, Coronary artery disease, Previous hospital admission, More than six doctors visit, Diabetes
(Capelastegui et al., 2009)	Jul 2003 Jun 2007	P	30-day admission-related & admission-unrelated	CAP	Sample size: 1,117; Galdako Hospital, Spain	7.3%	Cox proportional Hazard regression models	Pneumonia related: Treatment failure, Instability factors upon discharge Pneumonia unrelated: Age >65, Charlson index>2, Decompensated comorbidities
(Demir, Chaussalet, Xie, & Millard, 2008)	1997-2004	R	All types	COPD, Stroke, CHF	Sample size: COPD: 696,911; Stroke: 546,406; CHF: 533,439; The Department of Health in England's Hospital Episode Statistics	COPD: 39% Stroke: 21% CHF: 36%	Coxian phase-type distribution fitting via maximum likelihood Bayesian classification	Optimal time windows: COPD: 45 days Stroke: 16 days CHF: 39 days
(Fleming & Haney, 2013)	1999-2002	R	30-days	Hip fractures	Sample size: 41331; Medicare patients (≥65 years old); National Medicare and VA	18.3%	Logistic regression	Men, Long inpatient stay, Elixhauser comorbidities

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(Glasgow et al., 2010)	Oct 2003 Sep 2008	R	30-days all-cause Readmission to any VA hospital	General medicine patients	Sample size: 1,930,947; 32,819 AMA patients; Specified in patients left AMA; Veteran Administration Hospital	11% (patients who discharged home) 17.7% (AMA patients)	Multivariable Cox proportional hazards model	Discharge AMA, Age, Income Comorbidities (Arrythmia, dementia, fluid disorder, MI, psychosis, Non-white race
(Goldfield et al., 2008)	2005-2006	R	15 days index admission related Readmission to same& any hospital	All types	Sample size: 4,311,653; 249 Florida inpatient hospitals	6.% (15 days, same hospital) 7.9% (15 days, any hospital)	-	Reason for admission, Severity of illness, Extremes of age, Presence of mental health diagnoses, Substance abuse problems
(Greenblatt et al., 2010)	1992-2002	R	30-days Readmission to any hospital	Patients who had colectomy	Sample size: 42,348; Surveillence, Epidemiology, and End Results (SEER)-Medicare database (Age≥66)	11%	Multivariate logistic regression	Male, Asian/Pacific race, Region, Prior hospitalization, Comorbidity, Emergent admission, Prolonged hospital stay, Blood transfusion, Ostomy, Postoperative complication, Discharge to SNF, Hospital procedure volume (negatively)
(Halfon et al., 2002)	Jan 1997 Dec 1997	P	31-day	All types	Sample size: 3,474; Centre Hospitalier Universitaire Vaudois, Switzerland	23%	Stepwise selection beased on Wald statistic	Previous hospitalization, Long LOS, High Charlson comorbidity index, Surgical stay and low

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								Charlson score (negative)
(Hannan et al., 2003)	Jan 1999 Dec 1999	R	30-days CABG related statewide readmission	CABG	Sample size: 16325; New York State's Cardiac Surgery Reporting System	15.3%	Stepwise logistic regression	Older age, Women, Having larger body surface area, Having a myocardial infarction, Comorbidities (hepatic failure, dialysis), Hospital annual surgery volume < 100, Hospitals with high risk-adjusted mortality rates, Discharge to SNF, Longer LOS
(Hansen et al., 2011)	2006-2007 (survey data); 2008 (readmission rates)	R	30-day risk-standardized	AMI, HF, Pneumonia	Unit of analysis: Hospitals, Sample size: 67 hospitals. Patient Safety Climate in Healthcare Organizations survey data responses	-	Multiple regression	Hospital safety climate for AMI and HF(negatively).
(Hasan et al., 2010)	Jul 2001 Jun 2003	R	30-days all-cause, to index or another hospital	General medicine patients	Sample size: 7287 (derivation), 3659 (validation); Multicenter Hospitalist Study data	17.5%	Multivariable logistic regression	Insurance type, Marital status, Having a regular physician, Charlson index, Physical Medical Outcomes, Admissions in last year, LOS longer than 2 days

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(Hendryx et al., 2003)	1997	R	1-year statewide readmission	Psychiatric patients	Sample size: 1384; Harborview Medical Center, Seattle, Washington State Department of Social and Health Services , Mental Health Division database	8.2% (Depression: 1.5%; Bipolar disorder: 7.1%; schizophrenia: 16%; other: 8.8%)	Continuous variables: Least-squares linear; Categorical variables: Maximum-likelihood logistic multiple regression	Substance abuse, Global assessment of functioning score, Prior hospitalization or outpatient service use , Age, Social support unreliability, Activity of daily living dysfunction
(Holloway & Thomas, 1989)	1980	R	31-days all-cause	All types	Sample size: 2946; National Medical Care Utilization and Expenditure Survey data	9.5% (all-cause) 3.1% (linked) 6.1% (same-condition)	Multiple logistic regression	Very high risk or high risk condition group for the index stay, Poor or fair health status, Surgery during the index stay to a patient with health-related activity limitations
(Jasti et al., 2008)	Feb 1998 Mar 1999	R	30-days CAP-related Comorbidity-related	CAP	Sample size: 577; 7 hospitals in Pittsburg, Pennsilvania	12.00%	Multiple logistic regression	Low education level; Unemployment; Coronary artery disease; COPD
(Keenan et al., 2008)	2002-2005	R	30-days all-cause	HF	Sample size: 567,447; Medicare Standard Analytic Files, Medicare Enrolment Database (Age≥65)	23.6%	Hierarchical logistic regression	Age, Gender, 9 cardiovascular variables, 26 comorbidities

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(Krumholz et al., 2000)	1994-1995	R	6-months all-cause statewide readmissions	HF	Sample size: 1129(derivation), 1047(validation); Medicare patients (≥65 years old); 18 Connecticut Hospital	49% (all cause) 23% (HF-related)	Cox proportional Hazard models	Prior readmission within 1 year, Prior heart failure, Diabetes, Creatinine level>2.5 mg/dL
(Lagoe et al., 2001)	1998-1999	R	30-days unplanned same category diagnosis	CHF	Sample sizes: 465 (Crouse Hospital); 575 (St. Joseph's Hospital); 366(Community General Hospital)New York Statewide Planning and Research Cooperative System	9%(Crouse Hospital) 10.8% (St. Joseph's Hospital) 11% (Community General Hospital)	Manual stepwise regression	Crouse Hospital: Secondary diagnosis of cardiomyopathy or renal failure, 60 to 69 years old, inpatient stays of 6 days or more. St. Joseph's Hospital: Secondary diagnosis of renal failure and diabetes, 60 to 69 years old. Community General Hospital: Secondary diagnosis of renal failure and diabetes
(Lin, Chang, & Tseng, 2011)	Aug 2006 Dec 2008	P	30, 90, 180, and 360-days	acute stroke	Sample size: 2,657; community hospital in southern Taiwan	30-day – 10% 90-day – 17% 180-day – 24% 360-day – 36%	Kaplan-Meier method; Cox proportional hazard models	age, previous stroke, atrial fibrillation, coronary artery disease, complications at the index hospitalization, longer length of stay, dependency at discharge

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(Luthi et al., 2004)	Jun 1995 Sep 1996	R	21-months	HF (LVSD)	Sample size: 611; Medicare database (Age≥65),	70.0%	Bivariate analysis	Receiving no or low dose ACEI, prior MI, History of heart failure, Diabetes, Elevated creatinine level
(Luthi et al., 2003)	Jan 1999 Dec 1999	R	30-days all-cause	HF	Sample size: 1055; Three Swiss academic medical centers	13.2%	Multivariate logistic regression	None of the quality of care factors were significant
(Medress & Fleshner, 2007)	Aug 2001 Aug 2006	R	30-days unplanned, to index or another hospital	Patients who had colectomy	Sample size: 202; Cedars-Sinai Medical Center, Los Angeles	19.0%	Median comparison with Wilcoxon nonparametric test; Categorical variables' comparison: Fisher's exact test	No preoperative or surgical factor was associated with readmissions
(Mudge et al., 2010)	Feb 2006 Feb 2007	P	6-months unplanned	All types	Sample size: 142; Age≥50; Had prior two or more hospitalizations; Tertiary teaching hospital, Brisbane, Australia	39.0%	Multiple logistic regression	Chronic conditions, Body Mass Index, Depressive symptoms
(Neupane et al., 2010)	Jul 2003 Apr 2005	P	90-days all-cause	CAP	Sample size: 717; 2 Canadian cities; Age ≥65;	11.2%	Logistic regression	Male, Vitamin E supplement given

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(Onukwugha et al., 2011)	2000-2005	R	CVD-related, 7-day, 31-day, 180-day after discharge AMA, to the same hospital	CVD	Sample size: 348, 572; Maryland Health services Cost Review Commission	7-day: 2%; 31-day: 6%; 180-day: 14%	Generalized estimating equations regression	Discharge AMA, Age, Gender, Insurance type, Weekend discharge, HF, Drug abuse, PTCA, Race, Residence, Stroke, Alcohol abuse, CABG
(Philbin & DiSalvo, 1999)	1995	R	1-year	CHF	Sample size: 42731; Black and White race; New York State Department of Health Statewide Planning and Research Cooperative System database	21.3%	Logistic regression	Black race, Medicaid/Medicare insurance, Home helthcare services, Comorbidities, Use of telemetry monitoring Negative factors: Rural hospital, Discharge to SNF, Echocardiogram, Cardiac catheterization
(Tsuchihashi et al., 2001)	Jan 1997 Dec 1997	R	1-year CHF-related	CHF	Sample size: 230; 5 institutions in Fukuoka, Japan	35.0%	Multivariate logistic regression	Prior CHF admission, LOS, Hypertension, No occupation, Professional support, Poor follow-up visits
(van Walraven & Bell, 2002)	Mar 1999 Mar 2000	R	30-days unplanned	All types	Sample size: 2,403,181; Ontario Discharge Abstract Database	5.4%	Proportional Hazards Modeling	Discharge on Friday
(van Walraven et al., 2010)	Oct 2002 Jul 2006	P	30-day unplanned	All types	Sample size: 4,812; 11 Hospitals in Ontario	8% (Readmission & mortality rate)	Multivariable logistic regression	Length of stay (L), Acuity of the admission (A), Comorbidity of the patient (C), Emergency

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								department use (E)
(Weiss et al., 2010)	-	R	30-days unplanned	Medical-surgical patients	Sample size: 162 nurse-patient pairs; 4 Midwestern hospitals, Age>18	-	Logistic regression	Readiness for Hospital Discharge Scale-Nurse version-(inverse effect), Age, Medical type admission

R: Retrospective, P: Prospective, SNF: Skilled Nursing Facility, VA: Veterans Administration, LOS: Length of Stay, AMA: Against Medical Advice, LVSD: Left Ventricular Systolic Dysfunction, CHF: Congestive Heart Failure, HF: Heart Failure, COPD: Chronic Obstructive Pulmonary Disease, CAP: Community Acquired Pneumonia, CABG: Coronary Artery Bypass Graft, MI: Myocardial Infarction, ACEI: Angiotensin-Converting Enzyme Inhibitor, CVD: Cardiovascular Diseases, PTCA: Percutaneous Transluminal Coronary Angioplasty, HCAHPS: Hospital Care Quality Information from the Consumer Perspective

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Table 8: Focus of readmission prediction papers and common predictive factors, 1989 through 2010

Paper	Age	Gender	Comorbidity	Length of stay	Specific diagnosis/	Prior admissions	Race	Clinical	In-hospital process	Discharge process	Family/ support	Socio-economic	General health	Treatment	Admission process	Insurance	Quality of life
(Allaudeen et al., 2010)	x	x	x	x			x	x		x			x		x	x	
(Almagro et al., 2006)			x		x	x		x			x	x		x			x
(Beck et al., 2006)	x	x		x		x			x								
(Boult et al., 1993)	x	x				x	x				x	x	x				
(Capelastegui et al., 2009)	x		x	x	x	x		x	x				x	x			
(French et al., 2008)	x	x	x	x													
(Glasgow et al., 2010)	x	x	x				x					x					
(Greenblatt et al., 2010)	x	x	x	x	x	x	x	x	x	x	x	x		x	x		
(Halfon et al., 2002)	x	x		x	x	x				x				x			
(Hannan et al., 2003)	x	x	x	x	x		x	x	x					x		x	
(Hasan et al., 2010)			x	x		x					x					x	
(Heggestad & Lilleeng, 2003)				x													
(Hendryx et al., 2003)	x	x		x	x	x	x	x			x	x	x				x
(Hofer & Hayward, 1995)																	
(Holloway & Thomas, 1989)		x					x	x	x		x	x	x			x	
(Jasti et al., 2008))	x	x	x	x	x	x	x	x		x	x	x	x			x	
(Keenan et al., 2008)	x	x	x		x			x									

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(Krumholz et al., 2000)	x	x		x	x		x	x	x	x			x				
(Lagoe et al., 2001)	x	x	x	x	x		x			x	x	x	x				
(Luthi et al., 2003))	x	x	x		x	x	x							x			
(Luthi et al., 2004)	x	x			x	x			x					x			
(Medress & Fleshner, 2007)	x	x			x			x	x					x			
(Mudge et al., 2010)	x	x	x			x		x			x	x	x				x
(Neupane et al., 2010)	x	x	x		x			x			x	x		x			x
(Nasir et al., 2010)						x											
(Onukwugha et al., 2011)	x	x	x		x		x			x					x	x	
(Philbin & DiSalvo, 1999)	x	x	x	x			x		x	x					x		
(Tsuchihashi et al., 2001)	x	x	x	x	x	x				x	x	x	x		x		
(van Walraven & Bell, 2002)										x							
(van Walraven et al., 2010)	x	x	x	x		x			x	x	x				x		
Total	**24**	**24**	**18**	**16**	**16**	**15**	**14**	**13**	**10**	**11**	**12**	**11**	**10**	**9**	**7**	**7**	**4**

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References

Allaudeen, N., Schnipper, J. L., Orav, E. J., Wachter, R. M., & Vidyarthi, A. R. (2011). Inability of Providers to Predict Unplanned Readmissions. *J Gen Intern Med*. doi: 10.1007/s11606-011-1663-3

Allaudeen, N., Vidyarthi, A., Maselli, J., & Auerbach, A. (2010). Redefining Readmission Risk Factors for General Medicine Patients. *Journal of Hospital Medicine, 000*(000), 1-7.

Almagro, P., Barreiro, B., Ochoa de Echagüen, A., Quintana, S., Rodriguez Carballeira, M., Heredia, J., & Garau, J. (2006). Risk Factors for Hospital Readmission in Patients with Chronic Obstructive Pulmonary Disease. *Respiration, 73*(3), 311-317.

Andersen, H. E., Schultz-Larsen, K., Kreiner, S., Forchhammer, B. H., Eriksen, K., & Brown, A. (2000). Can Readmission After Stroke Be Prevented? : Results of a Randomized Clinical Study: A Postdischarge Follow-Up Service for Stroke Survivors. *Stroke, 31*(5), 1038-1045.

Anthony, D., Chetty, V. K., Kartha, A., McKenna, K., Rizzo DePaoli, M., & Jack, B. (2005). Re-engineering the Hospital Discharge: An Example of a Multifaceted Process Evaluation. In K. Henriksen, J. B. Battles, E. S. Marks, & D. I. Lewin (Eds.), *Advances in Patient Safety: From Research to Implementation* (Vol. 2, pp. 379-394). Rockville, MD: Agency for Healthcare Research and Quality.

Ashton, C. M., Kuykendall, D. H., Johnson, M. L., Wray, N. P., & Wu, L. (1995). The Association Between the Quality of Inpatient Care and Early Readmission. *Ann Intern Med, 122*(6), 415-421.

Ather, S., Chung, K. D., Gregory, P., & Demissie, K. (2004). The Association Between Hospital Readmission and Insurance Provider Among Adults With Asthma. *J Asthma, 41*(7), 703-707.

Appendix B (continued)

Bailey, E. J., Maclennan, C., Morris, P. S., Kruske, S. G., Brown, N., & Chang, A. B. (2009). Risks of Severity and Readmission of Indigenous and Non-Indigenous Children Hospitalised for Bronchiolitis. *J Paediatr Child Health, 45*(10), 593-597. doi: JPC1571 [pii]10.1111/j.1440-1754.2009.01571.x

Balaban, R. B., Weissman, J. S., Samuel, P. A., & Woolhandler, S. (2008). Redefining and Redesigning Hospital Discharge to Enhance Patient Care: A Randomized Controlled Study. *J Gen Intern Med, 23*(8), 1228-1233. doi: 10.1007/s11606-008-0618-9

Beck, C. E., Khambalia, A., Parkin, P. C., Raina, P., & Macarthur, C. (2006). Day of Discharge and Hospital Readmission Rates Within 30 Days in Children: A Population-Based Study. *Paediatr Child Health, 11*(7), 409-412.

Bell, C. M., Schnipper, J. L., Auerbach, A. D., Kaboli, P. J., Wetterneck, T. B., Gonzales, D. V., . . . Meltzer, D. O. (2009). Association of Communication Between Hospital-based Physicians and Primary Care Providers with Patient Outcomes. *J Gen Intern Med, 24*(3), 381-386. doi: 10.1007/s11606-008-0882-8

Benbassat, J., & Taragin, M. (2000). Hospital Readmissions as a Measure of Quality of Health Care: Advantages and Limitations. *Arch Intern Med, 160*(8), 1074-1081.

Berman, K., Tandra, S., Forssell, K., Vuppalanch, R., Burton, J. R., Jr., Nguyen, J., . . . Chalasani, N. (2011). Incidence and predictors of 30-day readmission among patients hospitalized for advanced liver disease. *Clinical Gastroenterology and Hepatology, 9*(3), 254-259. doi: S1542-3565(10)01107-9 [pii] 10.1016/j.cgh.2010.10.035

Bhalla, R., & Kalkut, G. (2010). Could Medicare Readmission Policy Exacerbate Health Care System Inequity? *Ann Intern Med, 152*(2), 114-117. doi: 0003-4819-152-2-201001190-00185 [pii]10.1059/0003-4819-152-2-201001190-00185

Bickmore, T. W., Pfeifer, L. M., & Jack, B. W. (2009). *Taking the Time to Care: Empowering Low Health Literacy Hospital Patients with Virtual Nurse Agents*. Paper presented at the Conference on Human Factors in Computing Systems, Proceedings of the 27th international conference on Human factors in computing systems, Boston, MA, USA. https://dl-web.dropbox.com/get/Readmissions/papers/2009_Reengineering Hospital Discharge A Protocol_Clancy.pdf?w=315d1abd

Bisognano, M., & Boutwell, A. (2009). Improving Transitions to Reduce Readmissions. *Frontiers of Health Services Management, 25*(3), 3-10.

Bodenheimer, T. (2008). Coordinating Care -- A Perilous Journey through the Health Care System. *N Engl J Med, 358*(10), 1064-1071. doi: 10.1056/NEJMhpr0706165

Boulding, W., Glickman, S. W., Manary, M. P., Schulman, K. A., & Staelin, R. (2011). Relationship between patient satisfaction with inpatient care and hospital readmission within 30 days. *Am J Manag Care, 17*(1), 41-48. doi: 12805 [pii]

Boult, C., Dowd, B., McCaffrey, D., Boult, L., Hernandez, R., & Krulewitch, H. (1993). Screening elders for the risk of hospital admission. *Journal of American Geriatric Society, 41*(8), 811-817.

Boutwell, A. (2011). Reduced Readmissions: Reform's Low-Hanging Fruit. *Healthcare Executive*, 86-88.

Bradley, E. H., Curry, L., Horwitz, L. I., Sipsma, H., Thompson, J. W., Elma, M., . . . Krumholz, H. M. (2012). Contemporary Evidence About Hospital Strategies for Reducing 30-Day ReadmissionsA National Study. *Journal of the American College of Cardiology, 60*(7), 607-614. doi: 10.1016/j.jacc.2012.03.067

Butler, J., & Kalogeropoulos, A. (2012). Hospital Strategies to Reduce Heart Failure ReadmissionsWhere Is the Evidence?. *Journal of the American College of Cardiology, 60*(7), 615-617. doi: 10.1016/j.jacc.2012.03.066

Capelastegui, A., Espana Yandiola, P. P., Quintana, J. M., Bilbao, A., Diez, R., Pascual, S., . . . Egurrola, M. (2009). Predictors of Short-term Rehospitalization Following Discharge of Patients Hospitalized with Community-Acquired Pneumonia. *Chest, 136*(4), 1079-1085. doi: chest.08-2950 [pii]10.1378/chest.08-2950

Appendix B (continued)

Chen, L. M., Jha, A. K., Guterman, S., Ridgway, A. B., Orav, E. J., & Epstein, A. M. (2010). Hospital Cost of Care Quality of Care, and Readmission Rates: Penny Wise and Pound Foolish? *Arch Intern Med, 170*(4), 340-346. doi: 170/4/340 [pii]10.1001/archinternmed.2009.511

Clancy, C. M. (2009). Reengineering Hospital Discharge: A Protocol to Improve Patient Safety, Reduce Costs, and Boost Patient Satisfaction. *Am J Med Qual, 24*(4), 344-346. doi: 1062860609338131 [pii]10.1177/1062860609338131

Clarke, A. (1990). Are Readmissions Avoidable? *BMJ, 301*(6761), 1136-1138.

Cline, C. M., Israelsson, B. Y., Willenheimer, R. B., Broms, K., & Erhardt, L. R. (1998). Cost Effective Management Programme for Heart Failure Reduces Hospitalisation. *Heart, 80*(5), 442-446.

Coleman, E. A., Parry, C., Chalmers, S., & Min, S. J. (2006). The Care Transitions Intervention: Results of a randomized control trial. *Arch Intern Med, 166*, 1822-1828.

Demir, E., Chaussalet, T. J., Xie, H., & Millard, P. H. (2008). Emergency Readmission Criterion: A Technique for Determining the Emergency Readmission Time Window. *IEEE Trans Inf Technol Biomed, 12*(5), 644-649. doi: 10.1109/TITB.2007.911311

Dormann, H., Neubert, A., Criegee-Rieck, M., Egger, T., Radespiel-Troger, M., Azaz-Livshits, T., . . . Hahn, E. G. (2004). Readmissions and Adverse Drug Reactions in Internal Medicine: the Economic Impact. *J Intern Med, 255*(6), 653-663. doi: 10.1111/j.1365-2796.2004.01326.xJIM1326 [pii]

Elixhauser, A., Steiner, C., Harris, D. R., & Coffey, R. N. (1998). Comorbidity Measures for Use with Administrative Data. *Medical Care, 36*(1), 8-27.

Epstein, C. D., Tsaras, G., Amoateng-Adjepong, Y., Greiner, P. A., & Manthous, C. (2009). Does Race Affect Readmission to Hospital After Critical Illness? *Heart & Lung, 38*(1), 66-76. doi: S0147-9563(08)00015-0 [pii]10.1016/j.hrtlng.2008.01.001

Appendix B (continued)

Fleming, M. O., & Haney, T. T. (2013). Improving patient outcomes with better care transitions: The role for home health. *Cleveland Clinic Journal of Medicine, 80*(e-Suppl 1), e-S2-e-S6. doi: 10.3949/ccjm.80.e-s1.02

French, D. D., Bass, E., Bradham, D. D., Campbell, R. R., & Rubenstein, L. Z. (2008). Rehospitalization After Hip Fracture: Predictors and Prognosis from a National Veterans Study. *J Am Geriatr Soc, 56*(4), 705-710. doi: JGS1479 [pii]10.1111/j.1532-5415.2007.01479.x

Friedman, B., & Basu, J. (2004). The Rate and Cost of Hospital Readmissions for Preventable Conditions. *Med Care Res Rev, 61*(2), 225-240. doi: 10.1177/1077558704263799

Glasgow, J. M., Vaughn-Sarrazin, M., & Kaboli, P. J. (2010). Leaving Against Medical Advice (AMA): Risk of 30-Day Mortality and Hospital Readmission. *J Gen Intern Med, 25*(9), 926-929. doi: 10.1007/s11606-010-1371-4

Goldfield, N. I., McCullough, E. C., Hughes, J. S., Tang, A. M., Eastman, B., Rawlins, L. K., & Averill, R. F. (2008). Identifying Potentially Preventable Readmissions. *Health Care Financ Rev, 30*(1), 75-91.

Gonzalez, A., Shih, T., Dimick, J. B., & Ghaferi, A. A. (2013). Does same-hospital readmission rate correlate with all-hospital readmission rate? *Journal of the American College of Surgeons, 217*(3), S105. doi: 10.1016/j.jamcollsurg.2013.07.240

Goodman, D. G., Fisher, E. S., Chang, C. H., Raymond, S. R., & Bronner, K. K. (2013). After Hospitalization:A Dartmouth Atlas Report on Readmissions Among Medicare Beneficiaries. In Robert Wood Johnson Foundation (Ed.), *The Revolving Door: A Report on U.S. Hospital Readmissions*.

Grafft, C. A., McDonald, F. S., Ruud, K. L., Liesinger, J. T., Johnson, M. G., & Naessens, J. M. (2010). Effect of Hospital Follow-up Appointment on Clinical Event Outcomes and Mortality. *Arch Intern Med, 170*(11), 955-960. doi: 170/11/955 [pii]10.1001/archinternmed.2010.105

Greenblatt, D. Y., Weber, S. M., O'Connor, E. S., LoConte, N. K., Liou, J. I., & Smith, M. A. (2010). Readmission After Colectomy for Cancer Predicts One-Year Mortality. *Ann Surg, 251*(4), 659-669. doi: 10.1097/SLA.0b013e3181d3d27c

Greenwald, J. L., Denham, C. R., & Jack, B. W. (2007). The Hospital Discharge: a Review of a High Risk Care Transition With Highlights of a Reengineered Discharge Process. *Journal of Patient Safety, 3*(2), 97-106.

Halfon, P., Eggli, Y., van Melle, G., Chevalier, J., Wasserfallen, J. B., & Burnand, B. (2002). Measuring Potentially Avoidable Hospital Readmissions. *J Clin Epidemiol, 55*(6), 573-587. doi: S0895435601005212 [pii]

Hannan, E. L., Racz, M. J., Walford, G., Ryan, T. J., Isom, O. W., Bennett, E., & Jones, R. H. (2003). Predictors of Readmission for Complications of Coronary Artery Bypass Graft Surgery. *JAMA, 290*(6), 773-780. doi: 10.1001/jama.290.6.773290/6/773 [pii]

Hansen, L. O., Williams, M. V., & Singer, S. J. (2011). Perceptions of hospital safety climate and incidence of readmission. *Health Serv Res, 46*(2), 596-616. doi: 10.1111/j.1475-6773.2010.01204.x

Harrison, P. L., Hara, P. A., Pope, J. E., Young, M. C., & Rula, E. Y. (2011). The impact of postdischarge telephonic follow-up on hospital readmissions. *Popul Health Manag, 14*(1), 27-32. doi: 10.1089/pop.2009.0076

Hasan, O., Meltzer, D. O., Shaykevich, S. A., Bell, C. M., Kaboli, P. J., Auerbach, A. D., . . . Schnipper, J. L. (2010). Hospital Readmission in General Medicine Patients: A Prediction Model. *J Gen Intern Med, 25*(3), 211-219. doi: 10.1007/s11606-009-1196-1

HealthleadersMedia. (2010). 20 People Who Make Healthcare Better. from http://www.healthleadersmedia.com/20people/

Heggestad, T., & Lilleeng, S. E. (2003). Measuring Readmissions: Focus on the Time Factor. *Int J Qual Health Care, 15*(2), 147-154.

Hendryx, M. S., Russo, J. E., Stegner, B., Dyck, D. G., Ries, R. K., & Roy-Byrne, P. (2003). Predicting Rehospitalization and Outpatient Services from Administration and Clinical Databases. *J Behav Health Serv Res, 30*(3), 342-351.

Hernandez, A. F., Greiner, M. A., Fonarow, G. C., Hammill, B. G., Heidenreich, P. A., Yancy, C. W., . . . Curtis, L. H. (2010). Relationship Between Early Physician Follow-up and 30-day Readmission Among Medicare Beneficiaries Hospitalized for Heart Failure. *JAMA, 303*(17), 1716-1722. doi: 303/17/1716 [pii]10.1001/jama.2010.533

Hines, A. L., Barrett, M. L., Jiang, H. J., & Steiner, C. A. (2014). Conditions with the Largest Number of Adult Hospital Readmissions by Payer, 2011;HCUP Statistical Brief #172. In Agency for Healthcare Research and Quality (Ed.). Rockville, MD.

Hofer, T. P., & Hayward, R. A. (1995). Can Early Re-Admission Rates Accurately Detect Poor-Quality Hospitals? *Med Care, 33*(3), 234-245.

Holloway, J. J., & Thomas, J. W. (1989). Factors Influencing Readmission Risk: Implications for Quality Monitoring. *Health Care Financ Rev, 11*(2), 19-32.

Institute for Healthcare Improvement. (2003). *Move Your Dot™: Measuring, Evaluating, and Reducing Hospital Mortality Rates (Part 1)*. White paper. Institute for Healthcare Improvement. Boston, MA. Retrieved from http://www.ihi.org/IHI/Results/WhitePapers/MoveYourDotMeasuringEvaluatingandReducingHospitalMortalityRates.htm

Institute for Healthcare Improvement. (2009a). Avoiding Readmissions: Optimizing the Transition from Hospital to Home. From http://www.ihi.org/IHI/Programs/ConferencesAndSeminars/HospitaltoHomeOptimizingtheTransitionJune09.htm

Institute for Healthcare Improvement. (2009b). Reducing Readmissions by Improving Transitions in Care Collaborative. *Collaboratives.* from

http://www.ihi.org/IHI/Programs/Collaboratives/IHICollaborative
IReducingReadmissionsbyImprovingTransitionsinCare.htm?TabId=0

Institute for Healthcare Improvement. (2010a). Good Heart Failure Care Follows Patients Home. 5. http://www.ihi.org/IHI/Topics/ChronicConditions/AllConditions/ImprovementStories/GoodHeartFailureCareFollowsPatientsHome.htm

Institute for Healthcare Improvement. (2010b). State Action on Avoidable Rehospitalizations (STAAR). from http://www.ihi.org/IHI/Programs/StrategicInitiatives/STateActiononAvoidableRehospitalizationsSTAAR.htm

Jack, B. W., Chetty, V. K., Anthony, D., Greenwald, J. L., Sanchez, G. M., Johnson, A. E., . . . Culpepper, L. (2009). A Reengineered Hospital Discharge Program to Decrease Rehospitalization: A Randomized Trial. *Ann Intern Med, 150*(3), 178-187. doi: 150/3/178 [pii]

Jack, B. W., Greenwald, J. L., Forsythe, S. R., O'Donnell, J. K., Johnson, A., Schipelliti, L., . . . Chetty, V. K. (2008). Developing the Tools to Administer a Comprehensive Hospital Discharge Program: The ReEngineered Discharge (RED) Program. In Agency for Healthcare Research and Quality (Ed.), (AHRQ Publication No. 08-0034-3 ed., Vol. 3, pp. 1-15).

Jacobs, B. (2011). Reducing heart failure hospital readmissions from skilled nursing facilities. *Prof Case Manag, 16*(1), 18-24. doi: 10.1097/NCM.0b013e3181f3f68401269241-201101000-00005 [pii]

Jasti, H., Mortensen, E. M., Obrosky, D. S., Kapoor, W. N., & Fine, M. J. (2008). Causes and Risk Factors for Rehospitalization of Patients Hospitalized with Community-acquired Pneumonia. *Clin Infect Dis, 46*(4), 550-556. doi: 10.1086/526526

Appendix B (continued)

Jencks, S. F., Williams, M. V., & Coleman, E. A. (2009). Rehospitalizations Among Patients in the Medicare Fee-for-Service Program. *N Engl J Med, 360*(14), 1418-1428. doi: 360/14/1418 [pii]10.1056/NEJMsa0803563

Jha, A. K., Orav, E. J., & Epstein, A. M. (2009). Public Reporting of Discharge Planning and Rates of Readmissions. *N Engl J Med, 361*(27), 2637-2645. doi: 361/27/2637 [pii]10.1056/NEJMsa0904859

Jiang, H. J., Russo, C. A., & Barrett, M. L. (2009). Nationwide frequence and costs of potentially preventable hospitalizations, 2006. In Agency for Healthcare Research and Quality (Ed.). Rockville, MD.

Jordan, C. J., Goldstein, R. Y., Michels, R. F., Hutzler, L., Slover, J. D., & Bosco, J. A. (2012). Comprehensive program reduces hospital readmission rates after total joint arthroplasty. *Am J Orthop, 41*(11), E147-151.

Joynt, K. E., & Jha, A. K. (2012). Thirty-Day Readmissions — Truth and Consequences. *New England Journal of Medicine, 366*(15), 1366-1369. doi: doi:10.1056/NEJMp1201598

Joynt, K. E., Orav, E. J., & Jha, A. K. (2011). Thirty-day readmission rates for Medicare beneficiaries by race and site of care. *JAMA, 305*(7), 675-681. doi: 305/7/675 [pii]10.1001/jama.2011.123

Jweinat, J. J. (2010). Hospital Readmissions Under the Spotlight. *J Healthc Manag, 55*(4), 252-264.

Kanaan, S. B. (2009). Homeward Bound: Nine Patient-Centered Programs Cut Readmissions (pp. 35): California HealthCare Foundation,.

Kartha, A., Anthony, D., Manasseh, C. S., Greenwald, J. L., Chetty, V. K., Burgess, J. F., . . . Jack, B. W. (2007). Depression is a Risk Factor for Rehospitalization in Medical Inpatients. *Prim Care Companion J Clin Psychiatry, 9*(4), 1-7.

Kasper, E. K., Gerstenblith, G., Hefter, G., Van Anden, E., Brinker, J. A., Thiemann, D. R., . . . Gottlieb, S. H. (2002). A Randomized Trial of the Efficacy of Multidisciplinary Care in

Appendix B (continued)

Heart Failure Outpatients at High Risk of Hospital Readmission. *J Am Coll Cardiol, 39*(3), 471-480. doi: S0735109701017612 [pii]

Keenan, P., Normand, S., & Lin, Z. (2008). An Administrative Claims Measure Suitable for Profiling Hospital Performance on the Basis of 30-Day All-Cause Readmission Rates Among Patients With Heart Failure. *Circ Cardiovasc Qual Outcomes, 2008*(1), 29-37. doi: 10.1161/CIRCOUTCOMES.108.802686

Koelling, T. M., Johnson, M. L., Cody, R. J., & Aaronson, K. D. (2005). Discharge Education Improves Clinical Outcomes in Patients With Chronic Heart Failure. *Circulation, 111*(2), 179-185. doi: 01.CIR.0000151811.53450.B8 [pii]10.1161/01.CIR.0000151811.53450.B8

Krumholz, H. M., Amatruda, J., Smith, G. L., Mattera, J. A., Roumanis, S. A., Radford, M. J., . . . Vaccarino, V. (2002). Randomized Trial of an Education and Support Intervention to Prevent Readmission of Patients With Heart Failure. *J Am Coll Cardiol, 39*(1), 83-89. doi: S0735109701016990 [pii]

Krumholz, H. M., Chen, Y.-T., Wang, Y., Vaccarino, V., Radford, M. J., & Horwitz, R. I. (2000). Predictors of Readmission Among Elderly Survivors of Admission with Heart Failure. *American Heart Journal, 139*(1), 72-77.

Krumholz, H. M., Merrill, A., & Schone, E. (2009). Patterns of Hospital Performance in Acute Myocardial Infarction and Heart Failure 30-Day Mortality and Readmission. *Circ Cardiovasc Qual Outcomes, 2009*(2), 407-413. doi: DOI: 10.1161/CIRCOUTCOMES.109.883256

Lagoe, R. J., Noetscher, C. M., & Murphy, M. P. (2001). Hospital Readmission: Predicting the Risk. *J Nurs Care Qual, 15*(4), 69-83.

Lappe, J. M., Muhlestein, J. B., Lappe, D. L., Badger, R. S., Bair, T. L., Brockman, R., . . . Anderson, J. L. (2004). Improvements in 1-year Cardiovascular Clinical Outcomes Associated with a Hospital-Based Discharge Medication Program. *Ann Intern Med, 141*(6), 446-453. doi: 141/6/446 [pii]

Appendix B (continued)

Lin, H. J., Chang, W. L., & Tseng, M. C. (2011). Readmission after stroke in a hospital-based registry: risk, etiologies, and risk factors. *Neurology, 76*(5), 438-443. doi: WNL.0b013e31820a0cd8 [pii]10.1212/WNL.0b013e31820a0cd8

Luthi, J. C., Burnand, B., McClellan, W. M., Pitts, S. R., & Flanders, W. D. (2004). Is Readmission to Hospital an Indicator of Poor Process of Care for Patients With Heart Failure? *Qual Saf Health Care, 13*(1), 46-51.

Luthi, J. C., Lund, M. J., Sampietro-Colom, L., Kleinbaum, D. G., Ballard, D. J., & McClellan, W. M. (2003). Readmissions and the Quality of Care in Patients Hospitalized with Heart Failure. *Int J Qual Health Care, 15*(5), 413-421.

Manning, S. (2011). Bridging the Gap Between Hospital and Home: A New Model of Care for Reducing Readmission Rates in Chronic Heart Failure. *J Cardiovasc Nurs, 00*(0), 0. doi: 10.1097/JCN.0b013e318202b15c

Marcantonio, E. R., McKean, S., Goldfinger, M., Kleefield, S., Yurkofsky, M., & Brennan, T. A. (1999). Factors Associated with Unplanned Hospital Readmission Among Patients 65 Years of Age and Older in a Medicare Managed Care Plan. *The American Journal of Medicine, 107*(1), 13-17.

Maurer, P. P., & Ballmer, P. E. (2004). Hospital Readmissions--Are They Predictable and Avoidable? *Swiss Med Wkly, 134*(41-42), 606-611. doi: smw-10706 [pii]2004/41/smw-10706

Medress, Z., & Fleshner, P. R. (2007). Can We Predict Unplanned Hospital Readmission After Colectomy for Ulcerative Colitis and Indeterminate Colitis? *Am Surg, 73*(10), 998-1001.

Miles, T. A., & Lowe, J. (1999). Are Unplanned Readmissions to Hospital Really Preventable? *J Qual Clin Pract, 19*(4), 211-214.

Moore, C., Wisnivesky, J., Williams, S., & McGinn, T. (2003). Medical Errors Related to Discontinuity of Care from an Inpatient to an Outpatient Setting. *JGIM: Journal of General Internal Medicine, 18*(8), 646-651. doi: 10.1046/j.1525-1497.2003.20722.x

Appendix B (continued)

Motamedi, S. M., Posadas-Calleja, J., Straus, S., Bates, D. W., Lorenzetti, D. L., Baylis, B., . . . Ghali, W. A. (2011). The efficacy of computer-enabled discharge communication interventions: a systematic review. *Qual Saf Health Care, 20*, 403-415. doi: bmjqs.2009.034587 [pii]10.1136/bmjqs.2009.034587

Mudge, A. M., Kasper, K., Clair, A., Redfern, H., Bell, J. J., Barras, M. A., . . . Pachana, N. A. (2010). Recurrent Readmissions in Medical Patients: a Prospective Study. *J Hosp Med, 2*(000), 61-67. doi:10.1002/jhm.811

Mudrick, D. W., Shaffer, L., Lalonde, M., Ruhil, A., Lam, G., Hickerson, J., . . . Snow, R. (2013). Cardiac Rehabilitation Participation Reduces 90-Day Hospital Readmissions after Acute Myocardial Infarction or Percutaneous Coronary Intervention. *Journal of the American College of Cardiology, 61*(10), E1418. doi: 10.1016/s0735-1097(13)61418-7

Nasir, K., Lin, Z., Bueno, H., Normand, S. T., Drye, E., Keenan, P. S., & Krumholz, H. M. (2010). Is Same-Hospital Readmission Rate a Good Surrogate for All-Hospital Readmission Rate? *Medical Care, 48*(5), 477-481.

Naylor, M. D., Brooten, D., Campbell, R., Jacobsen, B. S., Mezey, M. D., Pauly, M. V., & Schwartz, J. S. (1999). Comprehensive Discharge Planning and Home Follow-up of Hospitalized Elders: a Randomized Clinical Trial. *JAMA, 281*(7), 613-620. doi: joc80991 [pii]

Neupane, B., Walter, S. D., Krueger, P., Marrie, T., & Loeb, M. (2010). Predictors of Inhospital Mortality and Re-hospitalization in Older Adults with Community-Acquired Pneumonia: A Prospective Cohort Study. *BMC Geriatr, 10*(1), 22. doi: 1471-2318-10-22 [pii]10.1186/1471-2318-10-22

Olson, D. M., Bettger, J. P., Alexander, K. P., Kendrick, A. S., Irvine, J. R., Wing, L., . . . Graffagnino, C. (2011). *Transition of Care for Acute Stroke and Myocardial Infraction Patients: From Hospitalization to Rehabilitation, Recovery, and Secondary Prevention*. (11(12)-E011). Rockville, MD: AHRQ.

Appendix B (continued)

Onukwugha, E., Mullins, C. D., Loh, F. E., Saunders, E., Shaya, F. T., & Weir, M. R. (2011). Readmissions after unauthorized discharges in the cardiovascular setting. *Med Care, 49*(2), 215-224. doi: 10.1097/MLR.0b013e31820192a5

Ornstein, K., Smith, K. L., Foer, D. H., Lopez-Cantor, M. T., & Soriano, T. (2011). To the hospital and back home again: a nurse practitioner-based transitional care program for hospitalized homebound people. *J Am Geriatr Soc, 59*(3), 544-551. doi: 10.1111/j.1532-5415.2010.03308.x

Osei-Anto, A., Joshi, M., Audet, A. M., Berman, A., & Jencks, S. F. (2010). Health Care Leader Action Guide to Reduce Avoidable Readmissions. In Health Research & Educational Trust, The Commonwealth Fund, & John A. Hartford Foundation (Eds.). Chicago, IL.

Ouslander, J. G., Diaz, S., Hain, D., & Tappen, R. (2011). Frequency and Diagnoses Associated With 7- and 30-Day Readmission of Skilled Nursing Facility Patients to a Nonteaching Community Hospital. *J Am Med Dir Assoc, 12*(3), 195-203. doi: S1525-8610(10)00078-2 [pii]10.1016/j.jamda.2010.02.015

Patient Safety Authority. (2005). Unanticipated Care After Discharge from Ambulatory Surgical Facilities *PA-PSRS Patient Safety Advisory* (Vol. 2, pp. 1-32).

Philbin, E. F., & DiSalvo, T. G. (1999). Prediction of Hospital Readmission for Heart Failure: Development of a Simple Risk Score Based on Administrative Data. *J Am Coll Cardiol, 33*(6), 1560-1566. doi: S0735-1097(99)00059-5 [pii]

Press, M. J., Silber, J. H., Rosen, A. K., Romano, P. S., Itani, K. M. F., Zhu, J., . . . Volpp, K. G. (2010). The impact of resident duty hour reform on hospital readmission rates among medicare beneficiaries. *J Gen Intern Med, 24*(6), 405-411. doi: 10.1007/s11606-010-1539-y

Rayner, H. C., Temple, R. M., Marshall, T., & Clarke, D. (2002). A Comparison of Hospital Readmission Rates Between Two General Physicians With Different Outpatient Review Practices. *BMC Health Serv Res, 2*(1), 12.

Appendix B (continued)

Rich, M. W., Beckham, V., Wittenberg, C., Leven, C. L., Freedland, K. E., & Carney, R. M. (1995). A Multidisciplinary Intervention to Prevent the Readmission of Elderly Patients with Congestive Heart Failure. *N Engl J Med, 333*(18), 1190-1195. doi: 10.1056/NEJM199511023331806

Riegel, B., Carlson, B., Kopp, Z., LePetri, B., Glaser, D., & Unger, A. (2002). Effect of a Standardized Nurse Case-Management Telephone Intervention on Resource Use in Patients with Chronic Heart Failure. *Arch Intern Med, 162*(6), 705-712. doi: ioi10218 [pii]

Robert Wood Johnson Foundation. (2013). The Revolving Door: A Report on U.S. Hospital Readmissions.

Ross, J. S., Chen, J., Lin, Z., Bueno, H., Curtis, J. P., Keenan, P. S., . . . Krumholz, H. M. (2010). Recent National Trends in Readmission Rates After Heart Failure Hospitalization. *Circ Heart Fail, 3*(1), 97-103. doi: 10.1161/circheartfailure.109.885210

Santamour, B. (2011). Reining in Avoidable Readmissions *American Hospital Association* (pp. 8).

Simmons, J. (2010). Reducing Readmissions: Are Quality Payments a Carrot or Stick? *HealthLeaders Media,*, 2. https://dl-web.dropbox.com/get/Readmissions/papers/2010_Reducing Readmissions Are Quality Payments_Simmons.pdf?w=2d4e5880

Strunin, L., Stone, M., & Jack, B. (2007). Understanding Rehospitalization Risk: Can Hospital Discharge be Modified to Reduce Recurrent Hospitalization? *J Hosp Med, 2*(5), 1-22. doi: 10.1002/jhm.206

Taylor, M. (2010). Shutting the Door on Readmissions. *Hosp Health Netw, 84*(1), 33-34, 36.

Thomas, J. W., & Holloway, J. J. (1991). Investigating Early Readmission as an Indicator for Quality of Care Studies. *Medical Care, 29*(4), 377-394.

Trisolini, M., Aggarwal, J., Leung, M., Pope, G., & Kautter, J. (2008). Lessons Learned on Improving Quality and Efficiency in Health Care. In The Commonwealth Fund, Centers for Medicare and Medicaid Services, & Agency for Healthcare Research and Quality (Eds.), *The Medicare Physician Group Practice Demonstration* (pp. 58): The Commonwealth Fund, Centers for Medicare and Medicaid Services,.

Tsuchihashi, M., Tsutsui, H., Kodama, K., Kasagi, F., Setoguchi, S., Mohr, M., . . . Takeshita, A. (2001). Medical and Socioenvironmental Predictors of Hospital Readmission in Patients with Congestive Heart Failure. *American Heart Journal, 142*(4), E7-E7.

van Walraven, C., & Bell, C. M. (2002). Risk of Death or Readmission Among People Discharged from Hospital on Fridays. *CMAJ, 166*(13), 1672-1673.

van Walraven, C., Dhalla, I. A., Bell, C., Etchells, E., Stiell, I. G., Zarnke, K., . . . Forster, A. J. (2010). Derivation and Validation of an Index to Predict Early Death or Unplanned Readmission after Discharge from Hospital to the Community. *CMAJ*. doi: cmaj.091117 [pii]10.1503/cmaj.091117

van Walraven, C., Seth, R., Austin, P. C., & Laupacis, A. (2002). Effect of Discharge Summary Availability During Post-discharge Visits on Hospital Readmission. *J Gen Intern Med, 17*(3), 186-192. doi: jgi10741 [pii]

Vira, T., Colquhoun, M., & Etchells, E. (2006). Reconcilable Differences: Correcting Medication Errors at Hospital Admission and Discharge. *Qual Saf Health Care, 15*(2), 122-126. doi: 15/2/122 [pii]10.1136/qshc.2005.015347

Weinberger, M., Oddone, E. Z., & Henderson, W. G. (1996). Does Increased Access to Primary Care Reduce Hospital Readmissions? *The New England Journal of Medicine, 334*(22), 1441.

Weiss, M., Yakusheva, O., & Bobay, K. (2010). Nurse and Patient Perceptions of Discharge Readiness in Relation to Postdischarge Utilization. *Med Care, 48*(5), 482-486. doi: 10.1097/MLR.0b013e3181d5feae

Weissman, J. S., Ayanian, J. Z., Chasan-Taber, S., Sherwood, M. J., Roth, C., & Epstein, A. M. (1999). Hospital Readmissions and Quality of Care. *Med Care, 37*(5), 490-501.

Appendix B (continued)

Appendix C: Preventable Readmission Risk Factors for Patients with Chronic Conditions

Appendix C includes the article titled, "Preventable Readmission Risk Factors for Patients with Chronic Conditions", published in the Journal for Healthcare Quality.

Appendix C (continued)

Preventable Readmission Risk Factors for Patients With Chronic Conditions

Florentino Rico, Yazhuo Liu, Diego A. Martinez, Shuai Huang, José L. Zayas-Castro, Peter J. Fabri

Abstract: Evidence indicates that the largest volume of hospital readmissions occurs among patients with preexisting chronic conditions. Identifying these patients can improve the way hospital care is delivered and prioritize the allocation of interventions. In this retrospective study, we identify factors associated with readmission within 30 days based on claims and administrative data of nine hospitals from 2005 to 2012. We present a data inclusion and exclusion criteria to identify potentially preventable readmissions. Multivariate logistic regression models and a Cox proportional hazards extension are used to estimate the readmission risk for 4 chronic conditions (congestive heart failure [CHF], chronic obstructive pulmonary disease [COPD], acute myocardial infarction, and type 2 diabetes) and pneumonia, known to be related to high readmission rates. Accumulated number of admissions and discharge disposition were identified to be significant factors across most disease groups. Larger odds of readmission were associated with higher severity index for CHF and COPD patients. Different chronic conditions are associated with different patient and case severity factors, suggesting that further studies in readmission should consider studying conditions separately.

Keywords
rehospitalization
machine learning
risk factors
logistic regression
proportional hazard model

Introduction

The U.S. Federal Government is seeking to eliminate unnecessary care and to control growing spending by Medicare that reached $556 billion in 2012 (Rau, 2012). Readmission rates have been established as hospital performance measures with the objective of promoting quality, patient-centeredness, and accountability (CMS, 2013). Readmissions are a costly element of Medicare spending. Almost one fifth of the 11,855,702 Medicare beneficiaries who had been discharged from a hospital were readmitted within 30 days, and 34% were hospitalized within 90 days of which only 10% were likely to have been planned (Jencks et al., 2009). Moreover, the cost of readmissions is estimated at $26 billion annually for Medicare only, and $17 billion of it are potentially preventable (Robert Wood Johnson Foundation, 2013).

A hospital readmission can be defined as an admission to a hospital within a finite time frame after an original admission and discharge. A readmission can occur at either the same hospital or a different hospital, and it can involve planned or unplanned surgical or medical treatments (Stone and Hoffman, 2010). In general, preventable readmissions can be divided into three broad categories: complications or infections arising directly from the initial hospital stay, poorly managed transitions during discharge, and readmissions due to a chronic condition (Center for Healthcare Quality and Payment Reform, 2011).

The largest volume of readmissions occurs among patients with chronic conditions (Stone and Hoffman, 2010). According to Stone and Hoffman (2010), a number of factors might be contributing to this relatively high readmission rate: poor discharge planning and follow-up, low care instructions compliance, inadequate family support, disease complications, and medical errors. Thus, this study assesses readmission risk by chronic condition group to identify and compare significant factors associated with readmission.

There is still much that is unknown about which patient and hospital factors result in a higher probability of a hospital readmission. Hospital-based studies provide opportunities to identify these patients and improve the way hospital care is delivered (Center for Healthcare Quality and Payment Reform, 2011). Identifying the significant factors can help in the creation and implementation of interventions to target these specific conditions and high-risk patient groups.

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Literature Review

There is no standard definition of readmission in the literature. Kansagara and colleagues (2011) conducted a systematic literature review on risk prediction models for hospital readmissions. From this review, differences in the definition of readmissions are identified: the readmission time window (from 15 days to 12 months), type of hospital visit (all-included, potentially preventable, planned, or unplanned), source of data collection (administrative data, prospective clinical data collection, or real-time data collection), population and setting (age range, Medicare, Medicaid, 1 or multiple hospital networks, and departments within the hospital), and the medical condition under study. Although the definition of readmission varies across studies in the literature, most study analyses are driven by policy and decisions at the government level. The Centers for Medicare and Medicaid Services (CMS) annually defines and calculates 30-day readmission rates based on claims and administrative data for public reporting for acute myocardial infarction (AMI), heart failure (HF), and for pneumonia (CMS, 2013).

A number of studies measure readmission rates for specific medical conditions. Congestive heart failure (CHF) (Hamner and Ellison, 2005; Keenan et al., 2008; Kosiborod et al., 2003; Rosati et al., 1991), AMI, chronic obstructive pulmonary disease (COPD), pneumonia (Lindenauer et al., 2010), and type 2 diabetes are the most common diseases studied in readmissions models. However, other disease-specific readmission analyses include cancer (Greenblatt et al., 2010; Reddy et al., 2009) and sickle cell disease (Sobota et al., 2010; Frei-jones and Field, 2009). Studying readmissions and patients by disease group allows studies to use a more homogeneous cohort and implementation of interventions to reduce readmissions.

Logistic regression (LR) is the most commonly used classification technique in readmission research (Allaudeen et al., 2011; Bahadori et al., 2009; Berman et al., 2011; Callaly et al., 2010; Feudtner et al., 2009; Lindenauer et al., 2011; Nantsupawat et al., 2012; Neupane et al., 2010; Whitlock et al., 2010). A major reason for the widespread use of LR is its ease to adjust for different sampling schemes. Cox proportional regression models have also been implemented to assess the risk over time with the proportional hazards assumption. This method is able to identify statistically significant factors related to readmission and high-risk population groups (Capelastegui et al., 2009; Lau et al., 2001; Lipska et al., 2010), although they are limited in their ability to establish either cause and effect or the actual importance of these factors. Studies use both LR and Cox proportional regression models to find significant factors affecting readmission (Belfort et al., 2010; Khawaja et al., 2012; Strouse et al., 2008). Moreover, other studies (Alkalay et al., 2010; Bisgaard et al., 2011; Courtney et al., 2009) used univariate statistical analysis and hypothesis testing to identify significant differences between patients that were readmitted versus those that were not readmitted. The results in these models differ in determining which factors are significant. The variability and lack of consistency in the published relationships could be due to a large number of factors, many of which relate to statistical inference and cause–effect inference.

Readmission risk prediction continues to be difficult and current readmission predicting models perform poorly. Among published articles, the highest predicting ability, in terms of the area under the receiver operating characteristic, is 0.80 (Shulan et al., 2013). Limitations identified include the lack of generalizability of the results since most studies are done for a specific cohort of patients (Cline et al., 1998; Fontanella, 2008; Koelling et al., 2005; Rich et al., 1995), and the limitations of administrative data that may reduce the ability to identify predictors due to absence of important clinical information (Curtis et al., 2009; Frei-jones and Field, 2009; Reddy et al., 2009; Tsuchihashi et al., 2001). To provide more generalizable results, a representative sample size, and

Appendix C (continued)

relevant data, both clinical and administrative data are suggested (Kaben et al., 2008). However, it has been noted that adding additional risk factors has added complexity without improving the predictive power of models (Spiva et al., 2014).

There are still significant opportunities to advance the understanding of the causes and important risk factors associated with readmissions. The identification of high-risk patient groups could foster preventive interventions (Lin et al., 2011; Reddy et al., 2009), an area where predictive modeling could have a major impact. Although much work has been done to determine the most appropriate definition of readmission, our review shows that there is still no consensus on which readmission definition is best. Our definition of readmission is mostly based on the CMS definition of readmission, and the predictive models built presented in this study are used to identify risk factors, but not as a risk adjustment model. Thus, we believe that it makes sense to identify and predict in advance potentially preventable readmissions.

Purpose

The aims of this study are to identify potentially preventable readmissions based on claims and administrative data, to determine significant factors associated with the risk of being readmitted through a multivariate 30-day LR model and an extension of the Cox proportional hazard model with recurrent events, and to compare the effects of patient factors, case severity, and hospital factors associated with readmission across disease groups that are related to readmissions and their costs.

Study Design and Methods

The data used in this retrospective study are extracted from the administrative claims data of nine hospitals geographically localized within three adjacent counties in Florida. The types of hospitals in the study include general, teaching, and specialized hospitals. The initial dataset includes 594,751 patients accounting for 1,093,177 patient discharges from January 2005 through July 2012. The data were processed in three phases:

Phase I: Exclusion Criteria

The data were filtered based on the exclusion criteria in Table 1. This study excluded single events (admissions) or the entire patient record in the database to classify those readmissions that are avoidable and

Table 1. Excluded Single Admissions or Patient Records

Admissions	Patients
The record of the admission (single event) was excluded if it was due to:	The entire patient record was excluded if he/she was:
Continued care in the same hospital due to same-day internal hospital transfer (This was represented as a readmission in the same day in the database)	Discharged to hospice care
Newborn delivery	Diagnosed with cancer: *ICD-9* code "malignant neoplasm" and ongoing cancer treatment
Trauma	Diagnosed with renal disease and ongoing treatment
Rehabilitation	
Outside transfer and discharge planning is performed	
Elopement: leaving without medical advice and/or treatment	
Death and subsequent to death (i.e., organ donation)	

potentially unavoidable. The records excluded are considered to be routine, planned, or unavoidable. After this process, the final dataset has 470,147 patients and 763,289 hospitalizations with a 30.2% elimination rate.

Phase II: Study Cohort by Disease Type

This study focuses on admissions for specific chronic conditions or diseases that are known for high readmissions rates. Using the *International Classification of Diseases, 9th Revision, Clinical Modification* (*ICD-9-CM*), primary diagnosis code was used to identify admissions for CHF (codes 428.*,402.01, 402.91, 404.01, 404.03, 404.11, 404.13, 404.91, 404.93), COPD (codes 491.0, 491.1, 491.2, 491.20, 491.21, 490, 492, 496), AMI (codes 410.*), type 2 diabetes (codes 250.*2), and pneumonia (codes 480–483, 485–486, 510, 511.0, 511.1, 511.9 and a primary diagnosis of a pneumonia-related symptom [codes 780.6, 780.6, 786.00, 786.05, 786.06, 786.07, 786.2, 786.3, 786.4, 786.5, 786.51, 786.52, 786.7] and a secondary diagnosis of pneumonia, emphysema, or pleurisy) as index admissions for these 5 illnesses.

Phase III: Planned/Unplanned Readmissions

We used the definition of planned/unplanned readmissions stated in the Hospital-Wide All-Cause Unplanned Readmission Measure final report for CMS (Horwitz et al., 2008). Planned readmissions were defined as those in which one of a prespecified list of procedures took place. This analysis considered only unplanned admissions within 30 days as the outcome of interest in the predictive models. This time frame was used to follow the CMS readmission definition standards to estimate high readmission penalties.

Study Variables

The descriptive statistics for the data and variables' categories are shown in Table 2. After discussions with hospital experts, we classified the variables for this study in three categories: (1) "patient factors": age range, gender, marital status, race/ethnicity, and language; (2) "case severity factors": severity of illness (from 1 = *minor* to 4 = *extreme* as defined by 3M APR DRG; 3M Health Information Systems, 2008), behavioral health comorbidities (1 if present as a secondary diagnosis, 0 otherwise), Charlson comorbidity index (Charlson Co; calculated based on the comorbid conditions and severity; Charlson et al., 1994), and length of stay (LOS) (days); (3) "hospital factors": hospitalist (1 if present, 0 otherwise), payer class, discharge disposition, admission type, and year (over seven years).

Analytical Methods

A LR model and a proportional hazard model were used to identify statistically significant variables and assess their 30-day unplanned readmission relative risk and the readmission risk over time (hazard ratio [HR] for recurrent events).

Logistic Regression and 30-Day Readmission Risk. We built a LR model to predict an unplanned readmission within 30 days of discharge as a binary output variable (Y = 1, if readmitted within 30 days, or 0 otherwise). The results are interpreted using the quantity $\log\frac{p}{1-p}$ (the "log odds") to compare the relative risks among the different class levels of the independent variables. Goodness-of-fit is evaluated using the Hosmer–Lemshow statistic and cross-validation. A Wald test is used to test the statistical significance of each coefficient (β) in the model and to create the 0.95 confidence intervals (CIs).

Proportional Hazard Model With Recurrent Events. We applied a Cox proportional hazards extension to estimate effects of covariates which are reported as HRs. The motivation for using proportional hazard model with recurrent events is that 1 patient might

Table 2. Descriptive Statistics for Study Variables

	CHF	COPD	AMI	Pneumonia	Type 2 Diabetes
No. of patients	7,287	5,946	9,688	10,897	4,879
No. of admissions	9,590	7,921	11,210	12,130	6,158*
Patient factors					
Age					
18–45	4.83	4.61	6.07	16.62	24.90
45–55	9.76	14.97	16.88	14.64	22.73
55–65	13.54	24.07	23.07	14.95	19.31
65–75	17.02	25.08	19.86	15.34	15.43
75–85	27.82	21.78	21.08	21.73	12.11
85+	14.93	6.19	7.79	9.32	3.73
Null	12.10	3.31	5.25	7.40	1.78
Gender					
Female	51.41	56.93	41.28	55.90	49.97
Male	48.59	43.07	58.72	44.10	50.03
Marital status					
Divorced/Separated	11.29	19.88	10.34	11.83	16.29
Married	39.74	35.89	51.27	41.28	35.85
Single	21.30	23.65	22.75	27.13	35.62
Widowed	27.67	20.59	15.64	19.77	12.24
Race					
Black	15.21	8.98	6.17	11.78	28.28
Hispanic	8.08	4.94	8.26	8.68	12.85
White	75.31	84.86	82.40	77.71	56.94
Other	1.40	1.21	3.17	1.83	1.93
Language					
English	70.22	79.52	78.55	75.19	78.73
Other	29.78	20.48	21.45	24.81	21.27
Case severity factors					
Severity of illness					
1 = Minor	9.35	20.26	25.22	10.84	21.60
2 = Moderate	45.29	43.23	40.95	48.41	33.87
3 = Major	35.33	24.25	22.74	31.55	23.22
4 = Extreme	5.52	3.04	9.05	6.10	3.00
Null	4.52	9.22	2.03	3.10	18.30
Behavioral health comorbidity					
No	76.53	65.24	80.09	70.26	74.76
Yes	23.47	34.76	19.91	29.74	25.24
Charlson comorbidity					
0	15.90	0.00	34.87	28.12	10.02
1	24.59	47.54	31.01	37.00	32.97
2	22.90	26.70	16.76	18.10	18.27
3	15.45	12.08	8.18	7.64	15.61
4	9.69	6.77	4.30	4.43	10.56
5+	11.47	6.91	4.88	4.71	12.59
Length of stay (days)					
Mean (min, max)	4.6 (0, 19)	3.8 (0, 56)	4.1 (0, 78)	5.2 (0, 15)	3.8 (0, 90)

(*Continued*)

Appendix C (continued)

Table 2. (*Continued*)

	CHF	COPD	AMI	Pneumonia	Type 2 Diabetes
Hospital factors					
Hospitalist					
Yes	25.85	29.10	27.27	28.62	32.64
No	74.15	70.90	72.73	71.38	67.36
Payer class					
Commercial	9.49	10.96	26.52	18.39	19.96
Medicaid	10.32	14.47	8.26	12.56	21.14
Medicare	75.89	67.44	55.98	60.00	44.71
Other	4.30	7.13	9.24	9.05	14.19
Discharge disposition					
Nonacute facility	43.02	29.57	26.43	33.79	32.49
Routine/home	52.74	67.10	57.22	63.45	64.08
Specialty hospital	2.89	1.00	14.99	0.88	0.99
Other	1.35	2.34	1.36	1.88	2.44
Admission type					
Emergency	83.67	82.07	77.25	87.36	69.29
Routine	4.53	9.22	2.08	3.10	18.32
Urgent	6.61	3.64	9.22	4.23	5.31
Other	5.19	5.08	11.45	5.31	7.08
No of previous admissions					
Mean (min, max)	2.8 (1, 36)	3.3 (1, 45)	1.9 (1, 49)	2.4 (1, 59)	3.1 (1, 52)
Year					
H	19.26	13.26	14.89	16.07	14.31
I	16.03	12.11	13.31	14.55	13.41
J	13.23	12.02	15.58	13.72	13.30
K	13.69	14.76	16.33	14.06	14.70
L	12.40	17.04	14.99	15.00	15.54
M	14.58	17.28	14.59	15.42	15.85
N–O	10.81	13.53	10.31	11.19	12.89

*Includes 55 patients who are younger than 18 years.
AMI, acute myocardial infarction; CHF, congestive heart failure; COPD, chronic obstructive pulmonary disease.

have multiple records of admission during the seven years of data. Also, data might be heterogeneous across individuals and event dependent. Several survival models of recurrent events have been extended based on semiparametric Cox proportional hazard models (Gjessing et al., 2010). Based on the special features of the readmission problem, a conditional frailty model that combines a random effect with stratification of events is recommended (Box-Steffensmeier and De Boef, 2006). The model assumes that the contributions to the k^{th} admission are restricted to only those patients who have previously experienced the $k-1^{th}$ admission. The hazard of k^{th} event occurring for the i^{th} subject is

$$\lambda_{ik}(t; Z_{ik}) = \lambda_{0k}(t - t_{k-1})e^{\beta' Z_{ik}(x_{ik})+\omega_i}, \quad (1)$$

where X_{ik} and Z_{ik}, respectively, denote the observation time and covariate vector for the i^{th} subject with respect to the k^{th} event, and β is the unknown regression parameter vector. λ_{0k} is the baseline hazard rate and $(t - t_{k-1})$ represents the gap time between k^{th} and $k-1^{th}$ events. ω_i is the vector of random effects (frailties) across events.

Appendix C (continued)

Institutional Review Board Approval

This project was formally exempted by the University of South Florida Institutional Review Board because it does not meet the definition of human subjects research.

Results

The LR model and the conditional frailty proportional hazard model were built in SAS (version 9.3) and R (version 3.0.2), respectively. In the LR modeling predicting the 30-day risk of readmission, statistically significant variables are selected using a stepwise selection (entry = 0.10, stay = 0.10) removing insignificant variable from the model before adding a significant variable to the model in every step. For the proportional hazard model, variables are selected based on the level of statistical significance ($P \leq .10$) as well.

The statistically significant factors ($P \leq .05$) in the prediction of readmission varied across disease groups and prediction models, especially for patient and case severity factors. A large amount of hospital factors were found to be statistically significant ($P \leq .05$) in both models and across all diseases: accumulated number of admissions, year, and discharge disposition. The presence of a hospitalist and the discharge day of week were not found statistically significant in any of the models. The list of statistically significant factors found in each model across disease groups and the performance for the LR model, in terms of its discriminatory power (c-statistic), is presented in Table 3. The relative risks for the predictors' class levels are analyzed using the odds ratio (OR) from the LR model and the HR from the proportional hazard model. The OR and HR estimates are expressed as a ratio point estimate and the 0.95 CI upper and lower limits in Table 4.

Hospital Factors

The higher the accumulated times a patient has been readmitted to the hospital (OR from 1.06 to 1.15), the more likely it is that this person will be readmitted within 30 days. The OR and HR showed a consistent decreasing trend in readmission risk over the years in the data analyzed. Discharge disposition to another acute hospital or specialty hospital has the higher odds of being readmitted among other dispositions (routine home, nonacute facility, or other). Payer class was identified as significant for CHF, COPD, pneumonia, and type 2 diabetes. In most of the cases, patients with Medicaid and Medicare had the higher ratio (OR) of readmission among the payer classifications (commercial insurance). The type admission for the patient is considered for CHF, AMI, and type 2 diabetes; moreover, patients admitted as emergency have higher odds of readmission.

Case Severity Factors

Length of stay was statistically significant in across all disease groups, except for AMI. The more days the patient has stayed in the hospitals, the higher the likelihood of being readmitted with 30 days and risk of readmission over time. The proportional hazard model identified the Charlson comorbidity index as a significant factor in patients with CHF, AMI, Pneumonia and Type 2 Diabetes; moreover, patients with an index of 3 or higher have the highest odds of readmission HR over time (OR are also higher in this range for pneumonia and type 2 diabetes). Severity of illness index was included in one or both models for CHF, COPD, and pneumonia, and the odds of readmission increases as severity index is higher. Having a comorbidity related to a behavioral health condition was found for CHF patients, and the probability of readmission for having this comorbidity is 1.18 times higher than not having it.

Patient Factors

The differences of significant factors differed drastically across disease groups. The LR model found age to be significant only in the type 2 diabetes cohort. However, the proportional HR found it significant in four of the five disease groups. Gender was only included in the proportional hazard model, with higher HR for female patients.

Appendix C (continued)

Table 3. Significant Factors in Prediction Models

	CHF		COPD		AMI		Pneumonia		Type 2 Diabetes	
	30-Day Risk $c = 0.63$	Hazard Ratio	30-Day Risk $c = 0.68$	Hazard Ratio	30-Day Risk $c = 0.74$	Hazard Ratio	30-Day Risk $c = 0.67$	Hazard Ratio	30-Day Risk $c = 0.73$	Hazard Ratio
Patient factors										
Age		x		x				x	x	x
Language	x	x	x		x	x				
Marital status				x	x		x		x	
Race		x					x			x
Gender						x				
Case severity factors										
Behavioral health	x									
Severity of illness	x		x	x			x	x		
Length of stay	x		x	x			x	x	x	x
Charlson comorbidity		x				x	x	x	x	x
Hospital factors										
Hospitalist*										
Discharge day of week*										
Admission type		x			x				x	
Payer class		x	x	x			x	x		x
No. of previous admissions	x	x	x	x	x	x	x	x	x	x
Year	x	x	x	x	x	x	x	x	x	x
Discharge disposition	x	x	x	x	x	x	x	x	x	x

*Variable was not found significant by either model for the disease groups studied. It will not be included in the analysis of results.

AMI, acute myocardial infarction; CHF, congestive heart failure; COPD, chronic obstructive pulmonary disease.

Discussion

The objective of this study was to further understand the risk factors associated with unplanned readmissions within 30 days in prespecified disease cohorts. Using two predictive modeling techniques, we were able to identify and compare factors associated with the patient, hospital stay, and disease case severity.

Both the LR model and the proportional hazards model for 30-day readmission generate a different mix of significant risk factors in all five diseases. Thus, we performed analyses for readmission for specific diseases to better understand specific factors of a given disease. In most cases, factors were consistent across the specified diseases. For example, patients with commercial insurance always have lower risk of being readmitted, and longer LOS is associated with a higher probability of readmission. We found common significant factors across

Table 4. Model Parameter Relative Risks

	CHF		COPD	
	Odds Ratio	Hazard Ratio	Odds Ratio	Hazard Ratio
Patient factors				
Age				
18–45		1		1
45–55		0.94 (0.77–1.15)		1.52 (1.18–1.97)
55–65		0.78 (0.64–0.96)		1.6 (1.25–2.06)
65–75		0.73 (0.59–0.9)		1.46 (1.12–1.91)
75–85		0.78 (0.63–0.96)		1.27 (0.97–1.68)
85+		0.81 (0.65–1.01)		1.35 (0.98–1.85)
Gender				
Female				
Male				
Marital status				
Divorced				1
Married				0.84 (0.75–0.95)
Single				0.93 (0.82–1.05)
Widowed				0.98 (0.86–1.13)
Race				
Black		1		
Hispanic		0.86 (0.73–1.02)		
White		0.81 (0.73–0.91)		
Other		0.57 (0.38–0.85)		
Language				
English	1	1	1	
Other	1.17 (0.99–1.38)	1.13 (1–1.27)	1.27 (1.01–1.6)	
Case severity factors				
Disease severity				
1	1		1	1
2	1.23 (0.99–1.52)		1.17 (0.97–1.41)	0.99 (0.88–1.1)
3	1.32 (1.06–1.66)		1.39 (1.13–1.72)	1 (0.88–1.14)
4	1.33 (0.97–1.85)		1.62 (1.09–2.41)	0.94 (0.71–1.24)
Behavioral health comorbidity				
0	1			
1	1.18 (1.04–1.34)			

(*Continued*)

Appendix C (continued)

Table 4. (Continued)

	CHF		COPD	
	Odds Ratio	**Hazard Ratio**	**Odds Ratio**	**Hazard Ratio**
Charlson comorbidity				
0		1		
1		1.14 (0.99–1.3)		
2		1.22 (1.06–1.39)		
3		1.3 (1.12–1.51)		
4		1.34 (1.14–1.59)		
5+		1.26 (1.06–1.49)		
Length of stay (days)	1.02 (1–1.03)		1.04 (1.02–1.06)	1.03 (1.02–1.04)
Hospital factors				
Payer class				
Commercial		1	1	1
Medicaid		1.36 (1.14–1.62)	1.94 (1.45–2.6)	1.56 (1.3–1.87)
Medicare		1.23 (1.04–1.46)	1.44 (1.11–1.88)	1.38 (1.16–1.64)
Other		0.87 (0.68–1.11)	1.55 (1.09–2.22)	1.48 (1.19–1.84)
Accumulated number of admissions	1.15 (1.12–1.17)	1.08 (1.07–1.1)	1.15 (1.13–1.17)	1.09 (1.08–1.1)
Discharge disposition				
Nonacute facility	1	1	1	1
Routine/home	0.83 (0.73–0.93)	1.05 (0.96–1.15)	0.9 (0.77–1.05)	1.04 (0.94–1.16)
Specialty hospital	2.43 (1.85–3.2)	1.74 (1.4–2.17)	2.13 (1.27–3.58)	1.45 (0.98–2.15)
Other	1.59 (1.04–2.44)	1.27 (0.93–1.72)	1.78 (1.21–2.62)	1.58 (1.21–2.06)
Admission type				
Emergency		1		
Other		0.8 (0.65–0.99)		
Routine		0.83 (0.7–0.98)		
Urgent		0.87 (0.73–1.04)		
Year				
1	1	1	1	1
2	0.88 (0.73–1.06)	0.86 (0.76–0.97)	0.96 (0.75–1.23)	0.91 (0.78–1.06)
3	0.77 (0.61–0.97)	0.83 (0.71–0.97)	0.88 (0.65–1.2)	0.84 (0.72–0.98)
4	0.84 (0.66–1.05)	0.84 (0.71–0.98)	0.85 (0.63–1.15)	0.79 (0.68–0.91)
5	0.72 (0.57–0.92)	0.7 (0.6–0.83)	0.78 (0.58–1.04)	0.69 (0.6–0.81)
6	0.76 (0.6–0.96)	0.74 (0.63–0.87)	0.72 (0.53–0.97)	0.62 (0.53–0.72)
7–8	0.57 (0.44–0.74)	0.43 (0.35–0.52)	0.54 (0.39–0.75)	0.3 (0.25–0.37)

(Continued)

Appendix C (continued)

Table 4. (*Continued*)

	AMI		Pneumonia		Type II Diabetes	
	Odds Ratio	Hazard Ratio	Odds Ratio	Hazard Ratio	Odds Ratio	Hazard Ratio
Patient factors						
Age						
18–45				1	1	1
45–55				1.07 (0.89–1.27)	1.8 (0.55–5.87)	1.01 (0.84–1.21)
55–65				1.03 (0.86–1.23)	1.03 (0.31–3.4)	0.68 (0.55–0.84)
65–75				0.84 (0.68–1.03)	1.52 (0.46–5.05)	0.67 (0.51–0.88)
75–85				0.79 (0.65–0.97)	1.8 (0.54–6)	0.73 (0.55–0.97)
85+				0.83 (0.66–1.05)	2.11 (0.61–7.37)	0.65 (0.43–0.98)
Gender						
Female		1				
Male		0.89 (0.79–1.01)				
Marital status						
Divorced	1		1		1	
Married	1.13 (0.95–1.36)		0.77 (0.64–0.92)		0.82 (0.65–1.03)	
Single	0.92 (0.75–1.12)		0.85 (0.7–1.03)		0.91 (0.72–1.14)	
Widowed	1.12 (0.91–1.39)		0.72 (0.59–0.89)		0.62 (0.44–0.87)	
Race						
Black			1			1
Hispanic			0.79 (0.6–1.04)			0.8 (0.64–1.01)
White			1.03 (0.85–1.24)			0.61 (0.34–1.08)
Other			0.85 (0.51–1.39)			0.95 (0.81–1.1)
Language						
English	1	1				
Other	1.19 (1.02–1.4)	1.13 (0.95–1.34)				
Case severity factors						
Disease severity						
1			1	1		
2			1.09 (0.86–1.39)	1.2 (0.99–1.45)		
3			1.32 (1.03–1.7)	1.36 (1.11–1.65)		
4			1.55 (1.12–2.16)	1.35 (1.04–1.77)		
Behavioral health comorbidity						
0						
1						

(*Continued*)

Table 4. (*Continued*)

	AMI		Pneumonia		Type II Diabetes	
	Odds Ratio	Hazard Ratio	Odds Ratio	Hazard Ratio	Odds Ratio	Hazard Ratio
Charlson comorbidity						
0		1	1	1	1	1
1		1.03 (0.9–1.19)	1.16 (0.98–1.36)	1.26 (1.1–1.44)	0.9 (0.62–1.3)	0.95 (0.73–1.24)
2		1.01 (0.85–1.19)	1.27 (1.05–1.53)	1.37 (1.18–1.6)	1.73 (1.19–2.5)	1.58 (1.2–2.07)
3		1.13 (0.9–1.42)	1.4 (1.11–1.77)	1.47 (1.22–1.78)	2.01 (1.38–2.91)	1.74 (1.32–2.29)
4		1.35 (1.03–1.78)	1.57 (1.2–2.06)	1.5 (1.2–1.89)	1.9 (1.28–2.83)	1.96 (1.46–2.63)
5+		1.03 (0.77–1.39)	1.55 (1.19–2.02)	1.56 (1.25–1.94)	1.87 (1.25–2.78)	1.67 (1.23–2.26)
Length of stay (days)			1.02 (1–1.03)	1.01 (1.01–1.02)	1.03 (1.01–1.04)	1.03 (1.02–1.04)
Hospital factors						
Payer class						
Commercial			1	1		1
Medicaid			1.6 (1.26–2.02)	1.73 (1.44–2.08)		1.51 (1.23–1.85)
Medicare			1.47 (1.21–1.78)	1.79 (1.5–2.14)		1.31 (1.06–1.63)
Other			1.02 (0.76–1.37)	1.02 (0.81–1.28)		1.07 (0.85–1.35)
Accumulated number of admissions	1.12 (1.09–1.15)	1.14 (1.09–1.18)	1.09 (1.07–1.11)	1.06 (1.05–1.08)	1.11 (1.09–1.12)	
Discharge disposition						
Nonacute facility	1	1	1	1	1	1
Routine/home	0.6 (0.52–0.69)	0.74 (0.65–0.85)	0.72 (0.62–0.82)	0.83 (0.74–0.93)	0.88 (0.72–1.07)	1.52 (1.09–2.1)
Specialty hospital	6.74 (5.82–7.81)	41.1 (33.99–49.7)	3.26 (2.14–4.97)	2.9 (1.98–4.26)	3.95 (2.21–7.04)	0.92 (0.8–1.07)
Other	1.1 (0.71–1.72)	1.36 (0.86–2.16)	1.62 (1.12–2.35)	1.55 (1.13–2.11)	2.15 (1.41–3.29)	3.35 (1.92–5.85)
Admission type						
Emergency	1				1	
Other	1.1 (0.78–1.55)				0.8 (0.62–1.04)	
Routine	0.73 (0.58–0.9)				0.9 (0.63–1.27)	
Urgent	0.84 (0.69–1.01)				0.73 (0.52–1.03)	
Year						
1	1	1	1	1	1	1
2	0.85 (0.7–1.04)	0.86 (0.7–1.06)	0.96 (0.78–1.17)	1.01 (0.87–1.18)	0.73 (0.55–0.98)	0.68 (0.55–0.84)
3	1 (0.81–1.24)	0.9 (0.71–1.13)	0.89 (0.72–1.1)	0.89 (0.76–1.04)	0.65 (0.48–0.87)	0.83 (0.67–1.02)
4	0.85 (0.69–1.06)	0.8 (0.64–1.01)	0.91 (0.74–1.12)	0.95 (0.81–1.11)	0.63 (0.47–0.84)	0.71 (0.57–0.87)
5	0.91 (0.73–1.14)	0.76 (0.6–0.96)	0.76 (0.61–0.93)	0.77 (0.65–0.91)	0.59 (0.44–0.79)	0.59 (0.48–0.73)
6	0.74 (0.59–0.93)	0.66 (0.51–0.84)	0.76 (0.62–0.94)	0.74 (0.62–0.87)	0.51 (0.38–0.69)	0.52 (0.41–0.65)
7–8	0.73 (0.57–0.94)	0.56 (0.43–0.75)	0.7 (0.55–0.88)	0.56 (0.45–0.68)	0.48 (0.35–0.66)	0.39 (0.3–0.51)

Ratio values are expressed as point estimate (0.95 confidence interval).
AMI, acute myocardial infarction; CHF, congestive heart failure; COPD, chronic obstructive pulmonary disease.

diseases: discharge disposition, Charlson comorbidity index, and number of previous admissions.

Interesting patterns are found for some factors. For instance, as LOS increases, risk of readmission increases. For a large number of potential factors (i.e., case severity), LOS can be a surrogate measure. In the scope of this study, we cannot explain this behavior, and more clinical information is needed to understand potential causation. People speaking languages other than English have higher risk of readmission. In the literature, it has been found that discharge instructions are important in the reduction of readmissions, and one can hypothesize that patients who do not speak English need better means of communication for their discharge instructions. In the case of the patients' age, different risk patterns are observed across diseases. For type 2 diabetes patients, younger to middle-aged patients have higher readmission risk than elderly patients. However, COPD patients between the ages of 45 and 65 years have higher risk than others.

Most of the significant variables found are reasonable. However, some results need further investigation. For example, for hospital factors, is payer class difference due to the socioeconomic status or the hospital systems? Commercial insurance holders have a lower chance of being readmitted compared with all other payer classes. Moreover, another study also found that commercial insurance holders to have lower odds of readmissions compared with Medicare and Medicaid (Kruse et al., 2013), and this might be due to common characteristics that a patient in this group share (e.g., age, healthy enough to be employed, and income). Payer class can be an estimator of the socioeconomic situation of the patients admitted. We also find that older patients have a lower chance to be readmitted in the case of CHF. One study (Kosiborod et al., 2003) shows that the use of transfusions or other treatments for patients with anemia aged 65 years or older with HF could be the reason for lower readmission rate. However, our study lacks information of treatment during the stay.

Limitations

Our study provides important insights into the hospital readmission problem based on a network of hospitals located in Florida over 7 years of data and patients older than 18 years. However, there are several limitations in our study. First, our dataset comes from the administrative data collected that does not contain complete clinical information for the admission. These hospitals are located in the same extended metropolitan area, which means that the study population cannot be generalized to other areas in the country. The unavailability of clinical records and medical tests limits our ability to evaluate other variables that may be more closely related to how the patient was treated during a hospital stay. We believe that lack of patient transfer and discharge information also hinders tracking patients' visits to other facilities outside the network. Finally, model performance was modest in terms of the *c*-statistic achieved by the models (c-statistics between 0.63 and 0.74), but this performance is comparable with current predictive models in the literature (Kansagara et al., 2011; Kruse et al., 2013).

Directions for Future Research

In future studies, predictive models should explore the addition of other clinical factors associated with the patient visit to the hospital. This might enhance the identification of risk factors beyond the administrative claims data. To improve accuracy and discriminatory power of predictive models, other machine learning tools can be used to exploit more data complexity (i.e., decision trees, random forest, and support vector machine). In the practice, this study suggests that hospital further evaluates potential interventions for specific patient population at higher risk of readmission. However, interventions are already being designed to address specific needs such as patient education and discharge protocols (Koelling et al., 2005; Manning, 2011; Younis et al., 2012), analysis of racial disparities to reduce readmission rates for a specific population (Joynt et al., 2011), and the impact of specific medical intervention pertinent to a given disease to reduce mortality and readmission rates (Curtis et al., 2009). Finally, to capture patient characteristics more precisely, competing risk models for the interactions, one, two, or more diseases can also be studied, since a large number of patients with disease combination could be at risk for all potential diseases.

Acknowledgments

The Authors would like to thank the anonymous reviewers for their valuable feedback and comments. There are no financial relationships with any organizations that might have an interest in the submitted work in the previous 3 years, and no other relationships or activities that could appear to have influenced the submitted work.

References

3M Health Information Systems. The 3M all patient refined DRG (APR DRG) classification system. 2008. Available at: www.3Mhis.com. Accessed March 3, 2014.

Alkalay, A.L., Bresee, C.J., & Simmons, C.F. Decreased neonatal jaundice readmission rate after implementing hyperbilirubinemia guidelines and universal screening for bilirubin. *Clin Pediatr (Phila)* 2010;49:830–833.

Allaudeen, N., Vidyarthi, A., Maselli, J., & Auerbach, A. Redefining readmission risk factors for general medicine patients. *J Hosp Med* 2011;6:54–60.

Bahadori, K., FitzGerald, J.M., & Levy, R.D., et al. Risk factors and outcomes associated with chronic obstructive pulmonary disease exacerbations requiring hospitalization. *Can Respir J* 2009;16:e43–e49.

Belfort, M., Clark, S.L., & Saade, G.R., et al. Hospital readmission after delivery: evidence for an increased incidence of nonurogenital infection in the immediate postpartum period. *Am J Obstet Gynecol* 2010; 202:35.e1–35.e7.

Berman, K., Sweta, T., & Forsell, K., et al. Incidence and predictors of 30-day readmission among patients hospitalized for advanced liver disease. *Clin Gastroenterol Hepatol* 2011;9:254–259. Available at: www.sciencedirect.com/science/article/pii/S1542356510011079. Accessed February 7, 2014.

Bisgaard, T., Kehlet, H., & Bay-Nielsen, M., et al. A nationwide study on readmission, morbidity, and mortality after umbilical and epigastric hernia repair. *Hernia* 2011;15:541–546.

Box-Steffensmeier, J.M., & De Boef, S. Repeated events survival models: the conditional frailty model. *Stat Med* 2006;25: 3518–3533.

Callaly, T., Hyland, M., & Trauer, T., et al. Readmission to an acute psychiatric unit within 28 days of discharge: identifying those at risk. *Aust Health Rev* 2010;34:282–285.

Capelastegui, A., España Yandiola, P.P., & Quintana, J.M., et al. Predictors of short-term rehospitalization following discharge of patients hospitalized with community-acquired pneumonia. *Chest* 2009;136:1079–1085.

Center for Healthcare Quality and Payment Reform. Reducing hospital readmissions. *Healthc Exec* 2011. Available at: www.chqpr.org/readmissions.html. Accessed February 10, 2013.

Charlson, M., Szatrowski, T.P., & Peterson Janey Gold, J. Validation of a combined comorbidity index. *J Clin Epidemiol* 1994;47: 1245–1251.

Cline, C.M., Israelsson, B.Y., & Willenheimer, R.B., et al. Cost effective management programme for heart failure reduces hospitalisation. *Heart* 1998;80:442–446. Available at: www.pubmedcentral.nih.gov/articlerender.fcgi?artid=1728835&tool=pmcentrez&rendertype=abstract. Accessed January 25, 2014.

CMS. Hospital quality Initiative: outcome measures. A federal government website managed by the centers for Medicare & Medicaid services. 2013. Available at: www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/HospitalQualityInits/OutcomeMeasures.html. Accessed January 3, 2014.

Courtney, M., Edwards, H., & Chang, A., et al. Fewer emergency readmissions and better quality of life for older adults at risk of hospital readmission: a randomized controlled trial to determine the effectiveness of a 24-week exercise and telephone follow-up program. *J Am Geriatr Soc* 2009;57:395–402.

Curtis, J.P., Schreiner, G., & Wang, Y., et al. All-cause readmission and repeat revascularization after percutaneous coronary intervention in a cohort of Medicare patients. *J Am Coll Cardiol* 2009;54:903–907.

Feudtner, C., Levin, J.E., & Srivastava, R., et al. How well can hospital readmission be predicted in a cohort of hospitalized children? A retrospective, multicenter study. *Pediatrics* 2009;123:286–293.

Appendix C (continued)

Fontanella, C. The Influence of clinical, treatment, and healthcare system characteristics on psychiatric readmission of adolescents. *Am J Orthopsychiatry* 2008;78:187–198.

Frei-jones, M.J., & Field, J.J. Risk factors for hospital readmission within 30 days: a new quality measure for children with sickle cell disease. *Pediatr Blood Cancer* 2009;2008: 481–485.

Gjessing, H.K., Røysland, K., Pena, E., & Aalen, O.O. Recurrent events and the exploding cox model. *Lifetime Data Anal* 2010; 16:525–546.

Greenblatt, D.Y., Weber, S.M., & O'Connor, E.S., et al. Readmission after colectomy for cancer predicts one-year mortality. *Ann Surg* 2010; 251:659–669.

Hamner, J.B., & Ellison, K.J. Predictors of hospital readmission after discharge in patients with congestive heart failure. *Heart Lung* 2005;34:231–239.

Horwitz, L., Lin, Z., & Herrin, J., et al. Readmission Measure Final Technical Report Submitted by Yale New Haven Health Services Corporation/Center for Prepared for Outcomes Research & Evaluation (YNHHSC/CORE). Available at www.qualitynet.org/dcs/ContentServer?c=Page&pagename=QnetPublic%2FPage%2FQnetTier4&cid=1219069855841. 2008: 11–33 Accessed November 12, 2013.

Jencks, S.F., Williams, M.V., & Coleman, E. Rehospitalizations among patients in the Medicare fee-for-service program. *N Engl J Med* 2009;360:1418–1428.

Joynt, K.E., Orav, E.J., & Jha, A.K. Thirty-day readmission rates for Medicare beneficiaries by race and site of care. *JAMA* 2011;305: 675–681.

Kaben, A., Corrêa, F., & Reinhart, K., et al. Readmission to a surgical intensive care unit: incidence, outcome and risk factors. *Crit Care* 2008;12:R123.

Kansagara, D., Englander, H., & Salanitro, A., et al. Risk prediction models for hospital readmission a systematic review. *JAMA* 2011; 306:1688–1698.

Keenan, P.S., Normand, S-.L.T., & Lin, Z., et al. An administrative claims measure suitable for profiling hospital performance on the basis of 30-day all-cause readmission rates among patients with heart failure. *Circ Cardiovasc Qual Outcomes* 2008;1:29–37.

Khawaja, F.J., Shah, N.D., & Lennon, R.J., et al. Factors associated with 30-day readmission rates after percutaneous coronary intervention. *Arch Intern Med* 2012;172:112–117.

Koelling, T.M., Johnson, M.L., Cody, R.J., & Aaronson, K.D. Discharge education improves clinical outcomes in patients with chronic heart failure. *Circulation* 2005;111: 179–185.

Kosiborod, M., Smith, G.L., & Radford, M.J., et al. The prognostic importance of anemia in patients with heart failure. *Am J Med* 2003; 114:112–119.

Kruse, R.L., Hays, H.D., & Madsen, R.W., et al. Risk factors for all-cause hospital readmission within 30 days of hospital discharge. *J Clin Outcomes Manage.* 2013;20:203–214.

Lau, A.C., Yam, L.Y., & Poon, E. Hospital readmission in patients with acute exacerbation of chronic obstructive pulmonary disease. *Respir Med* 2001;95:876–884.

Lin, H., Chang, W., & Tseng, M. Readmission after stroke in a hospital- based registry. *Neurology* 2011;76(5):438–43.

Lindenauer, P.K., Bernheim, S.M., & Grady, J.N., et al. The performance of US hospitals as reflected in risk-standardized 30-day mortality and readmission rates for Medicare beneficiaries with pneumonia. *J Hosp Med* 2010;5:E12–E18.

Lindenauer, P.K., Normand, S-.L.T., & Drye, E.E., et al. Development, validation, and results of a measure of 30-day readmission following hospitalization for pneumonia. *J Hosp Med* 2011;6:142–150.

Lipska, K.J., Wang, Y., & Kosiborod, M., et al. Discontinuation of antihyperglycemic therapy and clinical outcomes after acute myocardial infarction in older patients with diabetes. *Circ Cardiovasc Qual Outcomes* 2010; 3:236–242.

Manning, S. Bridging the gap between hospital and home: a new model of care for reducing readmission rates in chronic heart failure. *J Cardiovasc Nurs* 2011;26:1–9.

Nantsupawat, T., Limsuwat, C., & Nugent, K. Factors affecting chronic obstructive pulmonary disease early rehospitalization. *Chron Respir Dis* 2012;9:93–98.

Neupane, B., Walter, S.D., & Krueger, P., et al. Predictors of inhospital mortality and re-hospitalization in older adults with community-acquired pneumonia: a prospective cohort study. *BMC Geriatr* 2010; 10:22.

Rau, J. Hospitals face pressure to avert readmissions. *New York Times.* 2012;p D1. Available at: www.nytimes.com/2012/11/27/health/hospitals-face-pressure-from-medicare-to-avert-readmissions.html?_r=1&. Accessed February 10, 2014.

Reddy, D.M., Townsend, C.M., & Kuo, Y-.F., et al. Readmission after pancreatectomy for pancreatic cancer in Medicare patients. *J Gastrointest Surg* 2009;13:1963–1974; discussion 1974–1975.

Rich, M.W., Beckham, V., & Wittenberg, C., et al. A multidisciplinary intervention to prevent the readmission of elderly patients with congestive heart failure. *N Engl J Med* 1995;333:1190–1195.

Robert Wood Johnson Foundation. *The Revolving Door: A Report on U. S. Hospital Readmissions.* Lebanon, NH: The Dartmouth

Institute for Health Policy & Clinical Practice; 2013.

Rosati, R.J., Huang, L., Navaie-Waliser, M., & Feldman, P.H. Risk factors for repeated hospitalizations among home healthcare recipients. *J Healthc Qual* 1991;25:4–10; quiz 10–1. Available at: www.ncbi.nlm.nih.gov/pubmed/12659074. Accessed February 12, 2014.

Shulan, M., Gao, K., & Moore, C.D. Predicting 30-day all-cause hospital readmissions. *Health Care Manag Sci* 2013;16:167–175.

Sobota, A., Graham, D., Heeney, M.M., & Neufeld, E.J. Corticosteroids for acute chest syndrome in children with sickle cell disease: variation in use and association with length of stay and readmission. *Am J Hematol* 2010; 85:24–28.

Spiva, L., Hand, M., VanBrackle, L., & McVay, F. (2014), Validation of a Predictive Model to Identify Patients at High Risk for Hospital Readmission. *J for Healthcare Qual.* doi: 10.1111/jhq.12070. Accessed March 05, 2013.

Stone, J., & Hoffman, G.J. *Medicare Hospital Readmissions: Issues, Policy Options and PPACA.* 2010. Available at: www.ncsl.org/documents/health/Medicare_Hospital_Readmissions_and_PPACA.pdf. Accessed December 19, 2013.

Strouse, J.J., Takemoto, C.M., & Keefer, J.R., et al. Corticosteroids and increased risk of readmission after acute chest syndrome in children with sickle cell disease. *Pediatr Blood Cancer* 2008;50:1006–1012.

Tsuchihashi, M., Tsutsui, H., & Kodama, K., et al. Medical and socioenvironmental predictors of hospital readmission in patients with congestive heart failure. *Am Heart J* 2001;142:E7.

Whitlock, T.L., Repas, K., & Tignor, A., et al. Early readmission in acute pancreatitis: incidence and risk factors. *Am J Gastroenterol* 2010;105:2492–2497.

Younis, J., Salerno, G., & Chaudhary, A., et al. Reduction in hospital reattendance due to improved preoperative patient education following hemorrhoidectomy. *J Healthc Qual* 2012;35:24–29.

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Supported by the Regenstrief Foundation through the Regenstrief Center for Healthcare Engineering at Purdue University.

The authors declare no conflict of interest.

Appendix D: A User Needs Assessment to Inform Health Information Exchange Design and Implementation

Appendix D presents the article titled, "A User Needs Assessment to Inform Health Information Exchange Design and Implementation", published in BMC Medical Informatics and Decision Making.

Appendix D (continued)

Strauss *et al. BMC Medical Informatics and Decision Making* (2015) 15:81
DOI 10.1186/s12911-015-0207-x

BMC
Medical Informatics & Decision Making

RESEARCH ARTICLE Open Access

A user needs assessment to inform health information exchange design and implementation

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Abstract

Background: Important barriers for widespread use of health information exchange (HIE) are usability and interface issues. However, most HIEs are implemented without performing a needs assessment with the end users, healthcare providers. We performed a user needs assessment for the process of obtaining clinical information from other health care organizations about a hospitalized patient and identified the types of information most valued for medical decision-making.

Methods: Quantitative and qualitative analysis were used to evaluate the process to obtain and use outside clinical information (OI) using semi-structured interviews (16 internists), direct observation (750 h), and operational data from the electronic medical records (30,461 hospitalizations) of an internal medicine department in a public, teaching hospital in Tampa, Florida.

Results: 13.7 % of hospitalizations generate at least one request for OI. On average, the process comprised 13 steps, 6 decisions points, and 4 different participants. Physicians estimate that the average time to receive OI is 18 h. Physicians perceived that OI received is not useful 33–66 % of the time because information received is irrelevant or not timely. Technical barriers to OI use included poor accessibility and ineffective information visualization. Common problems with the process were receiving extraneous notes and the need to re-request the information. Drivers for OI use were to trend lab or imaging abnormalities, understand medical history of critically ill or hospital-to-hospital transferred patients, and assess previous echocardiograms and bacterial cultures. About 85 % of the physicians believe HIE would have a positive effect on improving healthcare delivery.

Conclusions: Although hospitalists are challenged by a complex process to obtain OI, they recognize the value of specific information for enhancing medical decision-making. HIE systems are likely to have increased utilization and effectiveness if specific patient-level clinical information is delivered at the right time to the right users.

Keywords: Health information technology, Health information exchange, Medical decision making, Hospital medicine, Medical record linkage, Computer communication networks, Continuity of patient care, Care coordination

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Background

In the United States, 125 million people live with chronic conditions [1], and most of them receive care from multiple health care providers [2]. For these patients, care coordination is a necessity. Without care coordination, patients may undergo avoidable procedures, receive contraindicated treatments and incur unnecessary costs [3, 4]. To foster care coordination, federal incentives have been in place since 2009 to promote health information exchange (HIE). HIE refers to the electronic movement of health-related information among health care organizations intended to facilitate a safer and more timely, efficient, effective and equitable delivery of care [5].

Mixed evidence supports the ability of HIE to add value to healthcare systems [6, 7], to detect patient safety issues [8, 9] and to reduce healthcare delivery time and redundant testing [10–16]. For instance, Bailey and colleagues found HIE reduces repeated imaging testing for back pain and headache admissions in emergency departments, but has a negligible effect on reducing costs [11, 12]. Frisse and colleagues found a negative association between HIE usage and hospital admissions, computerized tomography (CT) scans and laboratory tests [17]. Vest and Miller found better patient satisfaction levels in those hospitals with HIE versus those without HIE [18]. Nguyen and colleagues reported a perceived need by healthcare providers and social service providers for improved health information sharing [19]. In contrast, Overhage and colleagues found no significant effect of HIE on reducing testing and number of admissions [13]. Lang and colleagues found HIE use associated with duplication of specialty consultations, as well as no significant effect of HIE on reducing number of hospital admissions, length of stay and number of tests [20]. Finally, Hansagi and colleagues found HIE use improved physician satisfaction, but no significant effects were observed on the number of emergency department, primary care and specialty visits [21]. A potential reason for the mixed evidence, as suggested by recently published systematic reviews [6, 7], is that widespread adoption of HIE across the United States is still limited. To date, only 14 % of solo practices and non-primary care specialties, 30 % of hospitals, and 10 % of ambulatory clinics are engaged in an HIE, with typical rates of access from 2 to 10 % of patient visits [22–24]. Despite substantial progress in electronic medical record (EMR) adoption, physician engagement in HIE remains low in office settings [24].

Research revealing how health professionals use HIE systems to obtain information from other institutions can help improve HIE functionality and subsequently improve HIE utilization. Some have explored the user's interaction in ambulatory care situations [25]. Although early studies concentrated on identifying drivers and barriers for HIE adoption [18, 25–28], recent studies have shed light on HIE use patterns. For example, it has been found that physicians are more likely to access radiology reports than any other health professional [29, 30], and that all users engage with HIE systems in a minimal fashion by accessing only the select patient screen and the recent encounters summary screen [31]. Additionally, it has been shown that time constraints are an important barrier to HIE usage [27, 28, 32–34], which might result in health professionals being reluctant to engage in HIE. Based on these results, we suggest that tailoring the type of information displayed on the first screens of HIE systems by type of user (e.g., physician, nurse) and discipline (e.g., emergency medicine, pediatrics) might improve HIE utilization by providers. Furthermore, most prior studies were performed in emergency departments with providers already using HIE. New products often benefit from a user needs assessment before, during, and after the development cycle. We believe HIE systems will be more successful if they are developed with *a priori* input from its future users. Our work is unique as it provides a clinician needs assessment prior to HIE implementation, so the providers have not developed biases of using an HIE. Furthermore, our research expands the current evidence by focusing on an unexplored clinical setting in regards to HIE: an Internal Medicine (IM) Hospitalist Department.

In this study, we investigated an IM Department in a teaching hospital in Tampa, Florida before HIE implementation. Our objectives were to understand the process of obtaining medical information from other facilities prior to HIE, explore provider perceptions of the usage of outside information for medical decision-making, and to analyze their views on the potential impact of HIE. Improving HIE developers', policy makers', and administrators' understandings about how documents from outside institutions, referred to as outside information (OI), are collected and utilized by clinicians can inform HIE design and implementation which could improve HIE usability.

Methods

We used a convergent mixed-methods study design to gather insights about the performance of the current fax-based process to request OI, the use of OI for medical-decision making, and the physicians' perceptions of HIE implementation. We conducted semi-structured interviews with both IM third-year residents and attending physicians and performed direct observation of the workflows in the IM Department. In addition, we collected demographic and clinical data of hospitalizations that generated at least one request for OI. Institutional review board approval was granted for this study by the hospital's Office of Clinical Research and the University of South Florida (IRB Number: Pro00014574).

Study setting and datasets

This research was performed in the IM Department of a public, teaching hospital in Tampa, Florida. The hospital is a 1018-bed hospital serving 23 counties in Tampa using the electronic medical record system (EMR) Epic (EpiCare; Verona, WI) with no HIE functionality enabled. We considered three sources of data: direct observation, interviews, and the EMR. First, we observed approximately 750 h of the workflows and medical decision-process related to the request of OI. Second, we interviewed resident and attending physicians from the IM Department from January to February 2014. Finally, from the hospital's EMR, we extracted demographic and clinical factors for each hospitalization from October 2011 to March 2014 that generated at least one request for OI. We also extracted operational data related to the request for OI: timestamps for the request and receipt of OI, type of health professional requesting OI, and type of information received.

Process mapping

We followed a two-step method of observation and validation to document the process to request and collect OI. We created a process chart that represents the activities performed, resources used, and people involved in order to obtain OI. To construct these diagrams, our team of industrial engineers and physicians observed the process and created preliminary flow process charts. During observation, the team shadowed and interviewed medical teams, nurses and personnel from the medical records department. Three people each performed 30 observation periods. During each period, between 6 and 10 h were observed. Observations were performed every day of the week and during working hours. During these observations, between 3 and 5 providers were observed on both attending and resident physicians. Observers recorded their observations when necessary. The initial flow process charts were then validated by subject matter experts, which included physicians and the medical records department. We validated the process map during semi-structured interviews with the third year residents and attending physicians until saturation. During this validation process, we discussed perceived process times and any additional comments about each step in the process.

Interviews

A semi-structured interview (see Additional file 1) including 8 questions was performed with 16 physicians from the IM Department. All attending physicians in the IM Department and all third year resident physicians were e-mailed to be invited to participate in the study. We used a non-probabilistic convenience sampling approach. In an effort to reduce interviewer bias, a team member with expertise in interviewing methods prepared a 1-day training for the other members of the team. Additionally, the questions included in the interviews were discussed with subject experts to avoid potential bias imposed by the team. The duration of the interview was 30 min. An informed consent was reviewed and signed by each physician. Each interview was audio recorded and transcribed for posterior analysis. Afterwards, the de-identified transcripts were analyzed to code the main themes reported by the subjects using Atlas.ti version 6.0 [35]. The coding process was performed concurrently by three study members with experience in medicine, systems engineering, and qualitative analysis. In case of disagreement, the study members discussed the alternatives and a majority vote determined the final result.

Results

Interview respondents

Sixteen out of thirty-eight physicians participated (42.1 % response rate). The 16 study subjects included 11 third-year resident physicians and 5 attending physicians. There were an equal number of male and female subjects. On average, interviewees had been using the same EMR system for 2.5 years prior to the study. The 30-min interviews were transcribed and generated a free text document containing 37,579 words that was analyzed using Atlas.ti.

EMR data

Table 1 describes the hospitalizations for which OI was requested. The study population was 50.7 % female and 98.2 % English speaking followed by 4.5 % Spanish speaking preference. The mean age was 53.5 years old.

Pre-HIE process map of obtaining OI

Using the information collected from shadowing medical teams, interviewing physicians and meeting with medical records personnel, a final flow process chart was created (see Fig. 1). The boxes with curved bottoms represent steps in the process involving paper. Each step was separated depending on the person or location in which it took place. The current process to obtain outside records comprises eight steps, five paper generation steps, six decision points and at least four different personnel. The pre-HIE process flow chart demonstrates where HIE can improve the sharing of information. The process map shows that various individuals with different levels of medical expertise and in different locations are required to complete myriad steps at different times. Many steps involve paper documents to be generated and moved. For example, documents housed in one hospital need to be faxed page by page by an individual which generate another set of documents at the receiving hospital. Then, the duplicated paper documents are scanned into a computer,

Table 1 Demographic and clinical factors of hospitalizations with at least one request for outside information

	No. (%) $N = 2091$
Female	1061 (50.7)
Language preference	
English	1949 (93.2)
Spanish	95 (4.5)
Unknown/Other	47 (2.3)
Marital status	
Single	1361 (65.1)
Married	652 (31.2)
Unknown/Other	78 (3.7)
Primary care provider	1235 (59.1)
Payer class	
Commercial	627 (30)
Medicare	817 (39.1)
Medicaid	465 (22.2)
HCHCP	137 (6.6)
Other	45 (2.1)
Admission source	
Emergency room	1921 (91.9)
Physician-referral	84 (4)
Outside hospital	84 (4)
Other	2 (0.1)
	Mean (SD)
Age	53.5 (17.3)
Length of stay	6.7 (10)

HCHCP Hillsborough Country Health Care Plan

stored and later shredded. These actions require human and physical resources, as well as time. These types of waste could be largely replaced by a few clicks in an effectively designed HIE system.

Figure 2 represents a simplified flow process chart. Physicians believed that the time between identifying the need for OI and placing the request ranges between 1 min and 5 days, with a mode of 45 min. Our evaluation on the time actual orders to obtain HIE were entered into the EMR indicated that the median delay between admission and electronic order of OI request was 10-h. This demonstrates potential time that could be saved by effective HIE implementation if information was available immediately on admission to the hospital. Physicians estimated that the time between the request and when the information was viewed ranged between 1 and 72 h, with a mode of 18 h.

The interviews revealed that providers want alerts upon the arrival of OI. We found OI is sometimes faxed directly to the nurse's station or the hospital's Health Information Management Department depending on what information is sent with the request. When OI arrives, physicians must wait for the OI to be scanned into the hospital EMR to have access to the information, and must repeatedly check to see if the information is available. This suggests that effective HIE designs should include a feature to alert providers once OI is available for viewing. Another insight elicited through the interviews was that physician satisfaction with the OI received was higher among those who made follow-up phone calls to outside facilities to inquire about the record request. Also, physicians specifying exactly which data items they need in the OI request improved the value of the OI received.

Perceptions on use of OI compared to EMR data

To explore physicians' perceptions we asked, "What percentage of your patients do you request for OI?" Most physicians believe they request outside records for 5 to 10 % of their patients. We were able to compare the provider perceptions to the quantitative data and found that out of 15,230 admissions to the IM Department during the study timeframe, 2091 generated at least one request for OI (13.7 %). In addition, we were able to explore what factors influenced when the physician did not need OI. Responses to the question, "In which situations do you know OI exists but you do not request for records?" are presented in Table 2. Most physicians answered that if the current admission is unrelated to OI (i.e., "…it may be unrelated to the acute [issue] they are coming in for."), then they do not need that data. About 25 % of physicians reported that the process would take too long, so they did not feel it was useful to request the information (i.e., "I rarely request them because it's so difficult to get them. But I find it is usually not worth the time."). Most of the physicians (75 %) estimated that the information was not received or incorrect more than 33 % of the time. Our analysis of EMR data showed that in 814 out of 2091 (38.9 %) admissions, OI was requested but no documents were received.

The majority of physicians stated that the information received is often a large amount of data that is not organized for quick clinical use. The majority of physicians believed that between 33 and 66 % of all OI received is not useful. They elaborated that they might only be looking for specific data items, but an abundance of daily monitoring notes make it difficult to find relevant information. They also reported OI was not useful because it was not the information they had requested. See Table 2 for physician responses to the prompt: "Give examples in which outside information was requested and you encountered problems. What percentage?". This perception was compared to our findings from the data from the EMR. OI received from outside facilities are indexed as "medical record", "imaging", "history and physical", "note",

Appendix D (continued)

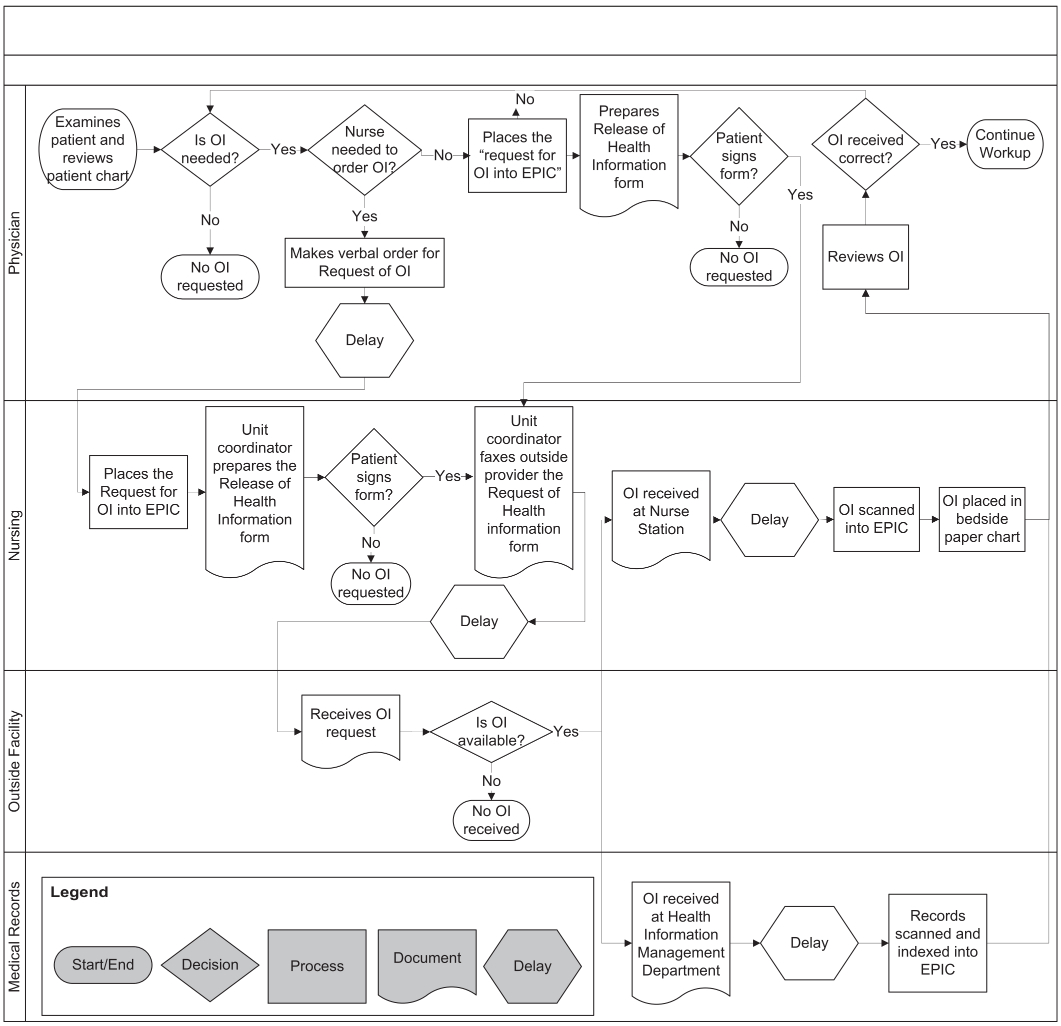

Fig. 1 Flow process chart of obtaining outside information. Abbreviations: OI, outside information

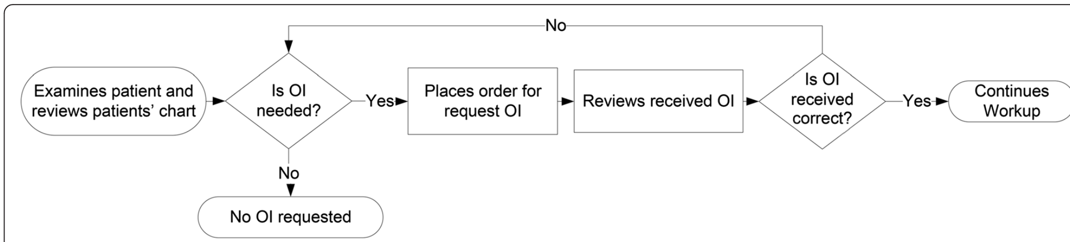

Fig. 2 Simplified flow process chart of obtaining outside information from physician perspective

Table 2 Summary of physician perceptions of current, pre-HIE use of outside information requested from outside hospitals

Reasons for not requesting	Problems encountered
1. Time	1. Process
• Outside information is too old	• Need to re-request
• Physician assumes the OI request process takes too long	• Delay in sending or scanning outside information after work hours
• Emergent situations	• Transitions-of-care communication problems
• Brief Hospital stay	• Problems with outside information transfer patients
	• Do not receive any outside information
	• OI comes too late
	• Delay waiting for imaging to be loaded from CD
	• Unaware of where outside information is in the process or if it has arrived
2. Relevance	2. Information
• Current admission unrelated to outside information	• Unhelpful physician or nursing notes
• Unnecessary to request outside information based on clinical expertise	• Difficulty finding useful information in unorganized and abundant amount of outside information
	• Skepticism of imaging or culture reads from outside facility
3. Patient	
• Patient or family is good historian and record keeper	
• Patient does not know where to request outside information from	

OI outside information

"discharge summary", "electrocardiogram", or "consultation". As shown in Table 3, most of the documents received were medical records ($n = 2343$) followed by imaging ($n = 567$) and history and physical ($n = 395$). Therefore, most received documents are labeled ambiguously as "medical records", consistent with physician perceptions that the OI is usually not useful. Mitigating an overabundance of data with efficient categorization of records is key for the successful future of HIE.

Physician-identified clinical drivers for future HIE use

Through our user needs assessment, we were able to identify common themes of clinical drivers for physicians requesting OI and medical decision-making using OI. By focusing on the drivers of OI requests, HIE designers and administration can work with clinicians to give physicians information they need at a time that it is clinically relevant. Physicians were asked, "In which specific clinical situations would timely OI influence your medical decisions?". The research team classified the clinical drivers for OI described by physicians into three groups: general, test-related, and health condition. As shown in Fig. 3, 10 out of 16 interviewed physicians reported "knowing previous workup or treatment", "medication reconciliation" and "comparing lab abnormalities" as clinical drivers where having OI may influence medical decisions. In general, physicians found OI most beneficial if the patient was unable to communicate and information was not available from family members.

Specific test-related clinical drivers for OI requests are presented in Fig. 4. Responses included imaging and laboratory tests. Imaging was the most frequently requested test, indicated by 11 of the 16 interviewed physicians. Specifically CT scan was identified by 6 physicians and magnetic resonance imaging (MRI) was identified by 6 physicians. Echocardiograms, cardiac catheterizations, electrocardiograms and troponin levels were mentioned by 10, 7, 4 and 1 of the 16 interviewed physicians, respectively. Bacterial cultures from urine, blood, or other sources were recognized as important to clinical decision-making by 7 physicians. Physicians also wanted specific information about blood cultures including speciation, antibiotic susceptibility and amount of bacteria present. Without this information, tests may need to be repeated and effective treatment is delayed or unnecessary treatment is provided.

Table 3 Document types received from outside health care facilities

Document type	Number of documents received (%) $N = 2091$
Medical record	1637 (78)
Imaging	383 (18)
History and physical	255 (12)
Note	206 (10)
Discharge summary	164 (8)
Electrocardiogram	153 (7)
Consultation	151 (7)

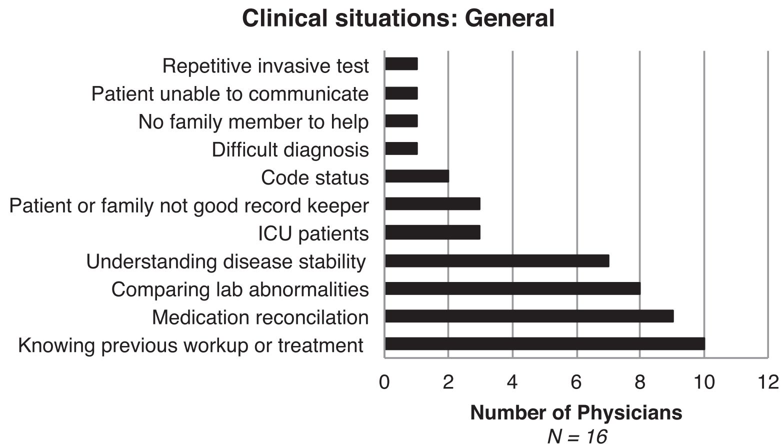

Fig. 3 Response distribution to the question "In which specific (general) clinical situations would timely OI influence your medical decisions?" Abbreviations: ICU, intensive care unit

Figure 5 shows the diverse health conditions that were identified as influential on medical decisions. The most frequently identified conditions were chest pain, acute cardiac conditions and infection, followed by kidney injury and cancer. 19 % of physicians discussed pneumonia and sepsis. Anemia was mentioned by 13 % of the interviewees. The remaining diagnoses were: thrombocytopenia, pulmonary hypertension, pulmonary embolism, malingering, lymphadenopathy, falls, Crohn's disease, acute respiratory distress, urinary tract infection, liver disease, identifying drug-seekers, altered mental status and chronic obstructive pulmonary disease.

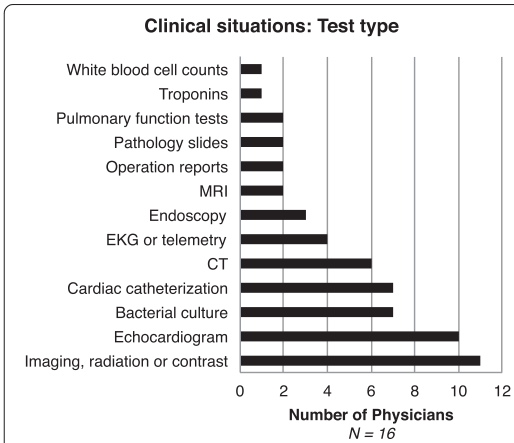

Fig. 4 Response distribution to the question "In which specific (test type) clinical situations would timely OI influence your medical decisions?" Abbreviations: MRI, magnetic resonance imaging; EKG, electrocardiogram; CT, computed tomography

Other critical clinical drivers for OI were admissions to the intensive care unit (ICU) and transfers from other hospitals. 19 % of physicians identified critically ill patients as key examples of when OI would be valuable. The physicians elaborated that knowing the prior work-up of a critically ill patient can expedite life-saving patient care decisions. Studies have shown that patients unable or unwilling to communicate their health status, which is common in the ICU, are targets for using HIE [26]. Additionally, patients transferred from other hospitals are an important population because they are often sicker patients with complex medical conditions. Information about the workup done at the originating hospital is critical to the receiving providers to provide effective care to the patient. Unfortunately, transitions of care are difficult in these situations because of the emergent nature and abundance of information. In our interviews, 50 % of the physicians recognized "hospital transfers" as an opportunity for using HIE, which is consistent with other reports [36]. Six interviewees identified that they frequently get incomplete OI in these cases, and five interviewees said there was poor communication with transfers.

Perceptions on pre-HIE electronic viewing of OI and potential for HIE

After discussion about situations where OI was influential in medical decisions, we wanted to explore how physicians physically interact with the outside records received. At the study hospital, outside documents are scanned into the EMR when they are received by fax, where they can then be viewed electronically. The original paper documents are stored in the patient's bedside chart for temporary access. Physicians were asked, "Do you view the majority of the outside records in paper or electronic

Appendix D (continued)

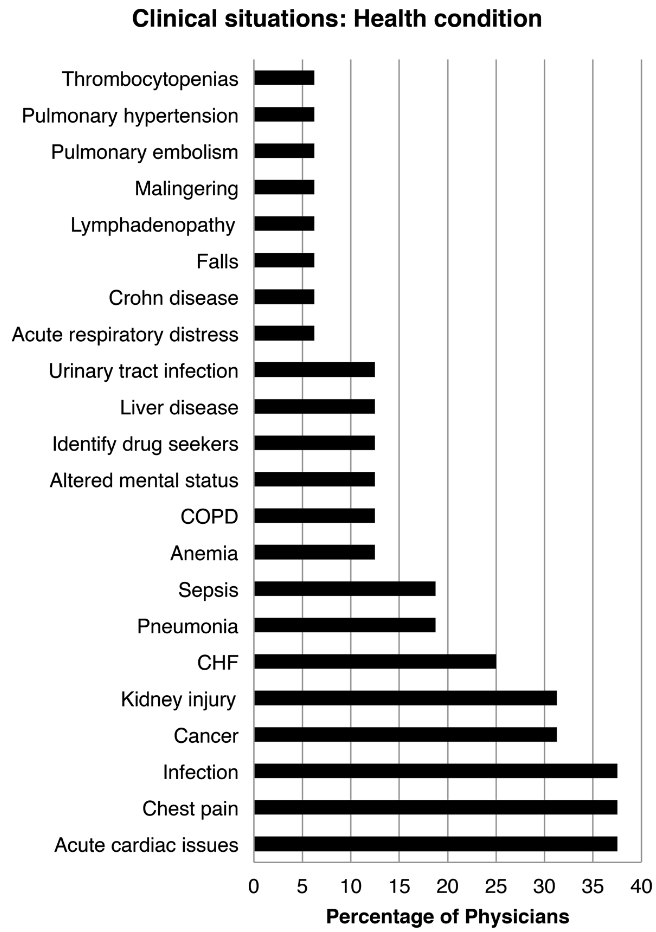

Fig. 5 Response distribution to the question "In which specific (health condition) clinical situations would timely OI influence your medical decisions?" Abbreviations: ICU, intensive care unit; COPD, chronic obstructive pulmonary disease; CHF, congestive heart failure

format? What percentage?". Then, a discussion was generated about the positives and negatives of viewing each format. Physicians responded that they view OI electronically less than 40 % of the time. The negative aspects identified for electronic viewing were "excessive clicking" and "it does not facilitate parallel tasking". Because there is limited screen space, it is difficult to view the outside documents while viewing current clinical information. Therefore, it is cumbersome to compare lab values or incorporate data into current documentation. Also, because of excessive amounts of records received and needing to adjust the zoom frequently to view content properly, the process requires extensive clicking. One of the benefits of electronic viewing was "remote access to records".

At the end of the interviews, we explored physicians' perceptions about HIE implementation in the future. Most physicians regarded HIE implementation positively; of the total number of responses to their perceptions about HIE, 85 % of the answers were coded as "positive". Most providers recognize the need for universal access to patient records and anticipate streamlined patient care. The most frequent positive responses were that HIE will "facilitate better patient care", lead to "less test redundancy" and "reduce costs". Some other perceptions were that HIE will "reduce patient harm", "decrease delays" and "improve transitions of care." One physician mentioned that it would only be "beneficial if done the right way." The negative feelings towards HIE were "concerns with HIPAA", "access to meaningless data" and "slow down patient care". This largely positive perception of the potential for HIE is an interesting contrast to providers that have experienced the problems of HIEs after implementation.

Discussion

Our study suggests that the drivers for HIE utilization are the treatment of complex patients with a high number of comorbidities or with frequent previous healthcare visits, consistent with previous research [27]. Our study identifies the difficulties faced by physicians in an IM Department in a large hospital in order to obtain outside information prior to HIE implementation and provides a user needs assessment to inform HIE design and implementation. Our research begins to address the gap identified by O'Malley and colleagues between the policy makers' expectations and the clinicians' experiences with HIE [37]. We identified information that is important to physicians in specific clinical situations. Finally, we provided physicians' insight into their perceptions of future implementation of HIE.

User needs assessment to inform HIE design

Our results suggest that efficient organization of data shared by HIE is paramount to effective use. Prior data showing low usage by providers may be partly due to the user-unfriendly nature of current HIE, which were designed without empiric *a priori* end-user input. Table 4 presents a design for the implementation of HIE informed by the results of our study. By identifying patterns in responses by the physicians, we were able to start creating networks of clinical drivers and important information needs to inform medical decision-making. An example clinical domain is congestive heart failure. Many physicians identified congestive heart failure as a condition in which specific OI, such as echocardiograms, electrocardiograms and weight measurements, likely influence clinical decisions and patient outcomes. This finding from the interviews is particularly important because the Centers for Medicare and Medicaid Services (CMS) require all congestive heart failure patients to have an up-to-date echocardiogram documented [38]. One of our recommendations is having visual indicators that alert the user when OI in the HIE is relevant to specific diagnoses within the local system. For example, if a provider were treating a patient with heart failure, the HIE would indicate that an echocardiogram is available from an outside hospital. These clinically relevant features of an HIE would promote provider satisfaction by facilitating their HIE interface experience and potentially improve compliance with quality measures.

Table 4 Design recommendations for health information exchange in an Internal Medicine Department in a public hospital

Design recommendations
1. Allow keyword search functionality in OI
2. Provide the telephone number of the OI source for follow up questions
3. Provide the list of previous medications for medication reconciliation
4. Facilitate remote access to patients' medical records
5. Provide computer screens that facilitate parallel tasking while reviewing documents electronically
6. Visual indicators for when OI is potentially relevant to specific diagnoses
7. Provide 1-click access to imaging, echocardiograms, bacterial cultures, cardiac catheterizations and CTs results (not only reports)
8. Prioritize OI access to patients with acute cardiac issues, chest pain, infection, cancer, and kidney injury
9. Prioritize OI access for hospital transfers and ICU patients

OI outside information, *CT* computerized tomography, *ICU* intensive care unit

Problems amenable to HIE and factors that will remain problematic

Our analysis of physician interviews identified problems amenable to HIE and factors that will remain problematic despite HIE implementation. Some factors that will be alleviated by HIE are the physician not requesting OI because they assume the process will take too long or yield incorrect information. The current fax based system is inefficient, so often providers proceed with less information. However, a well designed HIE could provide some information faster and more reliably. This will be helpful especially in critical situations, such as the ICU or hospital transfers. Another factor amenable to HIE is when the patient does not know from where to request OI. In some HIEs, the provider will be able to see the location of all OI. Also, the difficult process to find more information after initial review of OI will be mitigated because the provider will not need to fill out request forms, fax them again, and wait for their return (See Figs. 1 and 2). They will only require re-accessing HIE to find more information. The problem of not being able to get OI after office hours will be eliminated as the HIE will be automated without relying on personnel to manually fax information.

Some problematic factors that will remain despite HIE implementation are if the OI is old information and needs to be repeated despite having easy access to it. HIE will also be challenged by an abundance of unorganized information received if it is not designed properly. Viewing original radiology imaging may be slow using HIE, so the need for imaging disks may not be alleviated by HIE completely. There may still be skepticism of the results from outside facilities, which will lead to repetitive testing. Similarly, the HIE will only have final reports for bacterial cultures and there may still be doubt as to the laboratory techniques for certain results (i.e., which location cultures were drawn from).

Limitations & future work

Our study has limitations. First, the semi-structured interviews were a very powerful approach to obtain even subtle perceptions from the people who are involved in the process of requesting OI. However, by directly interviewing physicians, we are disturbing the environment and therefore the responses may be influenced by the presence of the research team. Second, because of the sample size and the specific setting (a teaching hospital using Epic), the conclusions obtained in this study may not be generalizable. However, this study represents an advance in the community of HIE knowledge since this research has not been carried out before in IM Departments within a hospital. Additionally, as of March 2015, Epic Systems is one of the top three EMR vendors comprising nearly 60 % of the market share of primary certified EMRs [39]. Future research should be done using a longitudinal approach, and ideally a larger number of settings. Finally, we also had attrition bias due to non-responses and we did not address any potential confounding due to user characteristics. For example, the level of computer skills may have biased physicians' responses. Nonetheless, all the interviewees had at least 2.5 years of experience in the same IM Department and with Epic.

There are various aspects that can be addressed in future work. First, the effect of provider access to clinically relevant OI on length of stay and resource utilization should be assessed. Linking OI to patient outcomes is key to demonstrating HIE value. Second, patients with abdominal pain and cardiac problems should be specifically explored since these patients represent a large amount of OI requests. Third, HIE research should focus on ICU patients or hospital transfer admissions, as others have explored the challenges of communication between hospitalists and primary care physicians [40].

Conclusion

By using mixed-methods we were able to map the current process of requesting OI, define provider perceptions, and compare those perceptions to quantitative data. This knowledge provides a user needs assessment for informing future HIE design and implementation. Further, our study combined with other research can direct future financial incentives to specifically promote evidence-based functionality that improves important outcomes. As meaningful use has improved EMR adoption, incentives for HIE paired with physician-guided implementation can likely improve the utilization of HIE.

Additional file

Additional file 1: Semi-structured interview: list of close- and open-ended questions used during the semi-structured interviews. (DOCX 23 kb)

Abbreviations

CHF: Congestive heart failure; CMS: Centers for Medicare and Medicaid Services; COPD: Chronic obstructive pulmonary disease; CT: Computerized tomography; EKG: Electrocardiogram; EMR: Electronic medical record; HIE: Health information exchange; ICU: Intensive care unit; IM: Internal medicine; MRI: Magnetic resonance imaging; OI: Outside clinical information.

Competing interests

None.

Authors' contributions

AS and DM contributed to the idea conception, study design, acquisition and analysis of qualitative and quantitative data. AG contributed to the study design and acquisition and analysis of qualitative data. CM and ST contributed to the study design and acquisition of qualitative and quantitative data. PF contributed to the analysis of quantitative and qualitative data. JZ is guarantor and contributed to the idea conception and study design. All authors contributed equally in preparing and reviewing multiple versions of the manuscript and provided important intellectual content. All authors read and approved the final version of this manuscript.

Acknowledgments

We would like to thank Peter Chang, Scott Arnold, Athena Muse and the physicians and nurses from hospital evaluated in this study for their contributions in this study. No funding was provided for the completion of this study.

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Received: 26 March 2015 Accepted: 5 October 2015
Published online: 12 October 2015

References

1. Anderson G, Knickman JR. Changing the chronic care system to meet people's needs. Health Aff. 2001;20:146–60.
2. Pham HH, Schrag D, O'Malley AS, Wu B, Bach PB. Care patterns in Medicare and their implications for pay for performance. N Engl J Med. 2007;356:1130–9.
3. Gandhi TK, Sittig DF, Franklin M, Sussman AJ, Fairchild DG, Bates DW. Communication breakdown in the outpatient referral process. J Gen Intern Med. 2000;15:626–31.
4. Jha AK, Chan DC, Ridgway AB, Franz C, Bates DW. Improving safety and eliminating redundant tests: cutting costs in U.S. hospitals. Health Aff (Millwood). 2009;28:1475–84.
5. Blumenthal D. Stimulating the adoption of health information technology. N Engl J Med. 2009;360:1477–9.
6. Rudin RS, Motala A, Goldzweig CL, Shekelle PG. Usage and effect of health information exchange: a systematic review. Ann Intern Med. 2014;161:803–12.
7. Rahurkar S, Vest JR, Menachemi N. Despite the spread of health information exchange, there is little evidence of its impact on cost, use, and quality of care. Health Aff (Millwood). 2015;34:477–83.
8. Ballard J, Rosenman M, Weiner M. Harnessing a health information exchange to identify surgical device adverse events for urogynecologic mesh. In: AMIA Annual Symposium proceedings, vol. 2012. 2012. p. 1109–18.
9. Kaelber DC, Bates DW. Health information exchange and patient safety. J Biomed Inform. 2007;40(6 Suppl):S40–5.

Appendix D (continued)

10. Kouroubali A, Starren JB, Clayton PD. Costs and benefits of connecting community physicians to a hospital WAN. In: AMIA Annual Symposium proceedings. 1998. p. 205–9.
11. Bailey JE, Wan JY, Mabry LM, Landy SH, Pope RA, Waters TM, et al. Does health information exchange reduce unnecessary neuroimaging and improve quality of headache care in the emergency department? J Gen Intern Med. 2012;28(2):176–83.
12. Bailey JE, Pope RA, Elliott EC, Wan JY, Waters TM, Frisse ME. Health information exchange reduces repeated diagnostic imaging for back pain. Ann Emerg Med. 2013;62:16–24.
13. Overhage JM, Dexter PR, Perkins SM, Cordell WH, McGoff J, McGrath R, et al. A randomized, controlled trial of clinical information shared from another institution. Ann Emerg Med. 2002;39:14–23.
14. Callen J, Paoloni R, Li J, Stewart M, Gibson K, Georgiou A, et al. Perceptions of the effect of information and communication technology on the quality of care delivered in emergency departments: a cross-site qualitative study. Ann Emerg Med. 2013;61:131–44.
15. Ozkaynak M, Brennan PF. Revisiting sociotechnical systems in a case of unreported use of health information exchange system in three hospital emergency departments. J Eval Clin Pract. 2013;19:370–3.
16. Thorn SA, Carter MA. The potential of health information exchange to assist emergency nurses. J Emerg Nurs. 2013;39:e91–6.
17. Frisse ME, Johnson KB, Nian H, Davison CL, Gadd CS, Unertl KM, et al. The financial impact of health information exchange on emergency department care. J Am Med Inform Assoc. 2012;19(3):328–33.
18. Vest JR, Miller TR. The association between health information exchange and measures of patient satisfaction. Appl Clin Inform. 2011;2:447–59.
19. Nguyen OK, Chan CV, Makam A, Stieglitz H, Amarasingham R. Envisioning a social-health information exchange as a platform to support a patient-centered medical neighborhood: a feasibility study. J Gen Intern Med. 2014;30(1):60–7.
20. Lang E, Afilalo M, Vandal AC, Boivin J-F, Xue X, Colacone A, et al. Impact of an electronic link between the emergency department and family physicians: a randomized controlled trial. CMAJ. 2006;174:313–8.
21. Hansagi H, Olsson M, Hussain A, Ohlén G. Is information sharing between the emergency department and primary care useful to the care of frequent emergency department users? Eur J Emerg Med. 2008;15:34–9.
22. Adler-Milstein J, Jha AK. Health information exchange among U.S. hospitals: who's in, who's out, and why? Healthcare. 2014;2:26–32.
23. Rudin R, Volk L, Simon S, Bates D. What affects clinicians' usage of health information exchange? Appl Clin Inform. 2011;2:250–62.
24. Furukawa MF, King J, Patel V, Hsiao C-J, Adler-Milstein J, Jha AK. Despite substantial progress in EHR adoption, health information exchange and patient engagement remain low in office settings. Health Aff (Millwood). 2014;33(9):1672–9. hlthaff.2014.0445.
25. Leu MG, Cheung M, Webster TR, Curry L, Bradley EH, Fifield J, et al. Centers speak up: the clinical context for health information technology in the ambulatory care setting. J Gen Intern Med. 2008;23:372–8.
26. Finnell JT, Overhage JM. Emergency medical services: the frontier in health information exchange. AMIA Annu Symp Proc. 2010;2010:222–6.
27. Vest JR, Zhao H, Jasperson J, Jaspserson J, Gamm LD, Ohsfeldt RL. Factors motivating and affecting health information exchange usage. J Am Med Inform Assoc. 2011;18:143–9.
28. Vest JR, Jasperson 'S, Zhao H, Gamm LD, Ohsfeldt RL. Use of a health information exchange system in the emergency care of children. BMC Med Inform Decis Mak. 2011;11:78.
29. Vest JR, Grinspan ZM, Kern LM, Campion TR, Kaushal R. Using a health information exchange system for imaging information: patterns and predictors. AMIA Annu Symp Proc. 2013;2013:1402–11.
30. Campion TR, Ancker JS, Edwards AM, Patel VN, Kaushal R. Push and pull: physician usage of and satisfaction with health information exchange. AMIA Annu Symp Proc. 2012;2012:77–84.
31. Vest JR, Jasperson 'S. How are health professionals using health information exchange systems? Measuring usage for evaluation and system improvement. J Med Syst. 2012;36:3195–204.
32. Ross SE, Schilling LM, Fernald DH, Davidson AJ, West DR. Health information exchange in small-to-medium sized family medicine practices: motivators, barriers, and potential facilitators of adoption. Int J Med Inform. 2010;79:123–9.
33. Wright A, Soran C, Jenter CA, Volk LA, Bates DW, Simon SR. Physician attitudes toward health information exchange: results of a statewide survey. J Am Med Inform Assoc. 2010;17:66–70.
34. Sicotte C, Paré G. Success in health information exchange projects: solving the implementation puzzle. Soc Sci Med. 2010;70:1159–65.
35. GmbH. ATLAS.ti version 6.2.23. [Computer Software]. Berlin, Germany. 2009. Licensed through University of South Florida.
36. Rudin RS, Salzberg CA, Szolovits P, Volk LA, Simon SR, Bates DW. Care transitions as opportunities for clinicians to use data exchange services: how often do they occur? J Am Med Inform Assoc. 2011;18:853–8.
37. O'Malley AS, Grossman JM, Cohen GR, Kemper NM, Pham HH. Are electronic medical records helpful for care coordination? Experiences of physician practices. J Gen Intern Med. 2010;25:177–85.
38. Physician Quality Reporting System. [http://www.cms.gov/Medicare/Quality-Initiatives-Patient-Assessment-Instruments/PQRS/index.html?redirect=/PQRS/]. Access date Oct 8 2015.
39. Electronic Health Record Vendors Reported by Hospitals Participating in the CMS EHR Incentive Programs,' Health IT Quick-Stat #29 [dashboard.healthit.gov/quickstats/pages/FIG-Vendors-of-EHRs-to-Participating-Hospitals.php]. Access date Oct 8 2015.
40. Hennrikus E. Communication between the primary care physician and the hospital at the time of patient admission. J Clin Outcomes Manag. 2012;19:453–9.

Appendix E: Uncovering Hospitalists' Information Needs From Outside Healthcare Facilities in the Context of Health Information Exchange Using Association Rule Learning

Appendix E exhibits the manuscript titled, "Uncovering Hospitalists' Information Needs From Outside Healthcare Facilities in the Context of Health Information Exchange Using Association Rule spotLearning", which is under review in Applied Clinical Informatics.

Appendix E (continued)

Uncovering Hospitalists' Information Needs from Outside Healthcare Facilities in the Context of Health Information Exchange Using Association Rule Learning

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Preprint Submitted to Applied Clinical Informatics

ABSTRACT

Background: Important barriers to health information exchange (HIE) adoption are clinical workflow disruptions and troubles with the HIE system interface. Prior research suggests that interfaces of HIE systems providing faster access to useful information may stimulate use and reduce barriers for adoption; however, little is known about informational needs of hospitalists.

Objective: Study the association between health problems and the type of information requested from outside healthcare providers by hospitalists of a tertiary care hospital.

Methods: We searched operational data associated with the fax-based exchange of patient information (previous HIE implementation) between hospitalists of an internal medicine department in a large urban tertiary care hospital in Florida, and any other affiliated and unaffiliated healthcare provider outside the hospital. All hospitalizations from October 2011 to March 2014 were included in the search. Strong association rules between health problems and the types of information requested during each hospitalization were discovered using Apriori algorithm, which were then validated by a team of hospitalists of the same department.

Results: Only 13.7% (2,089 out of 15,230) of the hospitalizations generated at least one request of patient information to other providers. The transactional data showed 20 strong association rules between specific health problems and types of information exist. Among the 20 rules, for example, abdominal pain, chest pain, and anemia patients are highly likely to have medical records and outside imaging results requested. Other health conditions, prone to have records requested, were lower urinary tract infection and back pain patients.

Conclusions: The presented list of strong co-occurrence of health problems and types of information requested by hospitalists from outside healthcare providers not only informs the implementation and design of HIE, but also helps to target future research on the impact of having access to outside information for specific patient cohorts. Our data-driven approach helps to reduce the typical biases of qualitative research.

Keywords: health information exchange; medical record linkage; medical decision making; hospital medicine; patient handoff; medical informatics applications.

Appendix E (continued)

1. INTRODUCTION

In the United States, people suffering from chronic health conditions constitute 49.8% of the adult population [1], and they consume 84% of the health care expenditures [2]. For people to achieve a safe, effective, and efficient health care, a coordinated effort is often required among unaffiliated providers. Lack of care coordination may lead to medication errors, avoidable hospital readmissions, duplicated testing, and delays in understanding the patient condition [3–10]. Since 2009, to support improvements in care coordination, the federal government has been stimulating the adoption and use of health information exchange (HIE). However, recent studies report HIE adoption across hospitals is still low [11,12]. As noted in the systematic review by Rudin and colleagues, one of the important barriers to HIE adoption are clinical workflow disruptions and troubles with the system interface [13]. Several authors claim better-designed interfaces for HIE systems would stimulate its usage since clinicians will have quicker access to useful patient information [14–16].

To improve HIE systems, it is imperative to understand physician information needs from outside health care facilities. Healthcare providers are increasingly constrained by the time they have to diagnose and treat patients, while trying to both follow evidence-based recommendations and consider the unique needs, characteristics, and preferences of the patients [17–22]. Given that the voluntary usage of additional information sources, such as HIE, can be discouraged by time constraints [23], there is a need to make the information displayed on HIE systems more valuable than the opportunity costs. For instance, screen redesign, single sign-on, enhanced record searches, or eliciting user needs could all be means to address the need. Additionally, the expected benefits of HIE might be fruitless if clinicians do not have access to a system that takes into account users' unique needs, cognitive tasks, and workflow processes [24]. However, there is no clear understanding and agreement of what data elements are needed from outside health care facilities to assist physicians in their decision-making [25].

Therefore, the information needs of the physicians are needed to inform the design and deployment of the HIE and health IT policy. Most of the published studies on physicians' information needs have focused on the communication between hospital-based (i.e., hospitalists) and primary care physicians [26]. However, in the context of HIE, the information sharing will include a bigger spectrum of healthcare providers. The communication between hospitalists and primary care providers has particular perspectives that may influence information needs and resource preferences.

Additionally, the collection of meaningful data on information needs may be problematic. Beyond the usual drawbacks of surveys and interviews, physician self-assessments of information-seeking behavior can be unreliable. For example, physicians may be unaware of their needs at the time of applying the self-assessment instrument. The information channels they use and their methods of using them, which are influenced by study habits adopted as early as medical school or college, may not provide the most efficient, accurate, and comprehensive information necessary for medical decision-making [27]. Many physicians are unaware of, or uncomfortable with, ever-evolving sources of information. In previous years, investigations have used questionnaires (e.g., [28–32]) and interviews (e.g., [33–36]) to shed light on physician's sources of information and how these influence workflow. Unfortunately, limited conclusions can be drawn from these data due to limitations in the internal validity and generalizability. In many of the investigations, for example, less than 50% of the sample population participated in the study.

This article reports the results of a study to document hospitalists' information needs in a large urban tertiary care hospital in Florida with no HIE functionality, and in planning stages for implementation. Our objective was to uncover associations between the health problems of the patient and the type of clinical information requested from outside health care facilities. An attempt was made to reduce selection and recall biases by mining a large number of data transactions from October 2011 to March 2014 of all hospitalists and residents working in the internal medicine department. Since other researchers have successfully used association rule learning (ARL) algorithms to analyze healthcare data (e.g., [37–39]), we implemented the Apriori algorithm to discover strong associations between the patients' health problems and the clinical information requested. The outcome of our investigation will help HIE developers and implementers recognize commonly requested clinical information from outside health care facilities by specific health problems, and thereby prioritize information display.

2. METHODS

The transactional data used in this study were collected from the Internal Medicine Department of Tampa General Hospital (TGH) in Tampa, Florida. TGH is a 1,018-bed tertiary care hospital serving over four million people from 23 counties in West Central Florida with no HIE functionality, and in planning stages for implementation. During the study timeframe, thre was no functional HIE in the region where TGH is located, and thereby most of the health information transactions between healthcare providers were performed via fax and telephone. A list of disease-information association rules was mined from transactional data using the Apriori algorithm, and validated by senior internists working at the same department. Transactional data includes all types of clinical information requested from outside healthcare providers during a patient hospitalization (denoted as *outside information*, OI) via fax and telephone, which was then scanned into the patient's electronic medical record. Our approach comprised four major phases: data collection and pre-processing, association rule building, post-processing and association rule selection, and clinical expert validation.

2.1. Data collection and pre-processing

Our dataset included all hospitalizations from October 2011 to March 2014 with at least one request for OI. The dataset was constructed with the list of health problems, and the list of OI requested in each hospitalization. The list of health problems corresponds to the discharge problem list, which are directly recorded by physicians during the patient hospitalization. We also collected demographic and clinical factors associated with each hospitalization. Independently, to assure consistency, three co-authors detected and corrected inaccurate health problem terms in the dataset. Any discrepancies between the co-authors were discussed and resolved by consensus, and uncertainty was referred to the fourth co-author.

2.2. Association rule building

We used ARL to discover strong associations between the health problems (antecedent) and OI requested (consequent). Since previous investigations found HIE useful only in particular cases [40], we hypothesize that a strong association between a health problem and an OI type indicates an important information need. Association rules are antecedents implying consequences of the form $X \rightarrow Y$, in our study, health problems implying OI requests. The association $X \rightarrow Y$ measures how likely the event Y is, given X. We measured the quality of an association rule in terms of *support* and *confidence*, and the quality of an association rule in terms of *lift*. *Support* corresponds to the statistical significance of a rule given by the proportion of transactions in the dataset containing a given set of health problems and OI types. A high support denotes a high popularity for the given set of health problems and OI types. *Confidence* is a measure of a rule's strength and is calculated as the conditional probability of the consequent given the antecedent, which is understood as the probability that a health problem occurs if it is known that a particular OI type was requested. *Lift* denotes the strength of the rule over the random co-occurrence of the antecedents and the consequent. Particularly, a lift greater than 1 implies the association between the set of health problems and the set of OI types is more significant than if the two sets were independent. In our context, an association rule with a lift value of 2 means that a physician who serves a patient with disease X is twice more likely to request outside information type Y than the general physician, and similarly, the physician who request Y is twice as likely to being serving a patient type X, since lift is a symmetric measure. The stronger the association is–the larger the lift. In epidemiological terms, support and confidence are related to the terms of prevalence and positive predictive value, respectively.

The association rules were mined using Apriori algorithm[41], which was executed in R using the Arules package[42]. Apriori calculates a set of strong rules given an arbitrarily selected minimum value for support and confidence. The strategy behind Apriori is to decompose the task of finding strong rules into two major subtasks; the frequent itemset generation and the rule generation. Frequent itemset generation finds those itemsets satisfying an arbitrarily selected minimum support value. On the other hand, rule generation extracts all the high-confidence rules from the previously generated frequent itemsets. These extracted rules are denoted as strong rules. Apriori algorithm assumes items within an itemset to be independent, and thereby it may disregard hidden interrelationships among items. This is important when dealing with many real-world applications, since the data under study are usually far from being perfect. For example, a distributed information environment with data being collected from different sources with imprecise and vague documentation methods. In our study, we assume that the dataset under study is precise and contain no ambiguity. We support this assumption in the fact that all data collected for this study were documented by highly trained individuals in a single EMR system. More precisely, hospitalists document the health problems during a hospitalization and coders from the hospital electronic medical records department document the OI types received from outside healthcare providers.

2.3. Post-processing and association rule selection

Once the set of strong rules was generated, we selected those in which both of the following conditions were satisfied: at least one health problem was present in the antecedent, and at least one OI type was present in the consequent. We denote these extracted rules as strong and potentially meaningful rules. Additionally, a chi-square test was utilized to determine the statistical significance of each association rule, where the rule-corresponding two-by-two table is given by the cells $X \cap Y$, $X^c \cap Y$, $X \cap Y^c$, and $X^c \cap Y^c$, where c refers to the complement of a given itemset. To facilitate calculations, we used the results of [43] to derive the chi-square value of each rule in terms of its support, confidence, and lift, and of the total number of data instances n. A p-value providing an upper bound on the type I error (i.e., the risk of discovering a rule that is actually false) of each rule is then computed from the chi square value by consulting the chi square distribution with one degree of freedom. Due to the high risk of type I error inherent to ARL algorithms, we adjusted the p-values to control for false discovery using an improved Bonferroni-type procedure: the Benjamini-Hochberg correction method[44]. This method allows us to control type I error during the identification of statistically significant rules in our exploratory study. Another approach to evaluate statistical significance of association rules is to test tentative rules on a validation dataset. However, this approach is problematic to use in exploratory studies, as in our context, due to the limited data availability. In our study, we consider those rules for which the chi square values lead to a corrected statistical significance level or type I error of 0.10 or lower to be statistically significant.

2.4. Clinical expert validation

We validated the set of strong and potentially meaningful rules with three internists from the TGH Internal Medicine Department. To assure consistency, the three internists independently assessed the set of rules generated by our research team. By consensus, any discrepancies between the internists were discussed and resolved. These validated rules are denoted as our final set of association rules.

3. RESULTS

3.1. Population and Dataset

Only 13.7% (2,089 out of 15,230) of the hospitalizations in the internal medicine department generated at least one request for OI. As shown in Table 1, 50.7% of the patients were female, with 93.2% English speakers followed by 4.5% Spanish speakers. Although 91.9% of the patients were admitted through the emergency department, most of them (59.1%) had a primary care provider at the time of their admission. The mean age was 53.5 years old, and the mean length of stay was 6.7 days.

Table 1. Demographic and clinical factors of hospitalizations, with at least one request for clinical information from outside healthcare providers, in the Internal Medicine Department of the Tampa General Hospital. Abbreviations: HCHCP, Hillsborough Country Health Care Plan.

N=2,089	**No. (%)**
Female	1,059 (50.7)
Language preference	
English	1,948 (93.2)
Spanish	94 (4.5)
Unknown/Other	47 (2.3)
Marital status	
Single	1,361 (65.1)
Married	650 (31.2)
Unknown/Other	78 (3.7)
Have a primary care provider	1,235 (59.1)
Payer class	
Commercial	627 (30)
Medicare	817 (39.1)
Medicaid	465 (22.2)

Appendix E (continued)

HCHCP	137 (6.6)
Other	45 (2.1)
Admission source	
Emergency room	1,919 (91.9)
Physician-referral	84 (4)
Outside hospital	84 (4)
Other	2 (0.1)
	Mean (SD)
Age	53.5 (17.3)
Length of stay	6.7 (10.0)

Hospitalists from the internal medicine department under study do no routinely collect OI, and if they do, the patient or their relatives have to authorize the released of patient information from outside healthcare facilities. As noted in Table 2, 75% of the requests for OI are made within 22 hours from patient admission and only 10% of the requests are made within 1 hour. Based on this data, the OI requests were not part of a routine during patient admission, and they seem to play an important role, perhaps, when the clinical picture of the patient becomes less clear than initially appeared. The most common health problems and OI requested in the 2,089 hospitalizations under study are presented in Table 3. The majority of the requests for OI were from rather non-specific health problems such as chest pain, 18.5%, abdominal pain, 15.1%, and dyspnea, 9.9%. This pattern is aligned with the patient population and clinical setting under study. On the other hand, the most frequent OI requested were outside medical records with 77.9%, followed by laboratory test results with 18.5% and imaging results with 18.2%. Important to note is that the frequency analysis presented in Table 3 may result in overlap between the different classes of health problems and outside information types.

Table 2. Analysis of duration from patient admission to when the request for OI was made by a hospitalist in the Internal Medicine Department of Tampa General Hospital.

Quantile	Duration in minutes	Duration in hours

100% Max	51,894	865
99%	18,456	308
95%	6,072	101
90%	3,534	59
75% Q3	1,309	22
50% Median	575	10
25% Q1	224	4
10%	49	1
5%	23	0
1%	0	0
0% Min	0	0

Table 3. Common health problems seen and outside information types requested during hospitalizations in the Internal Medicine Department of the Tampa General Hospital. Abbreviations: COPD, congestive obstructive pulmonary disease; CHF, congestive heart failure; EKG, electrocardiogram; GI, Gastrointestinal.

Health Problems	**Number of hospitalizations (%)**
Chest pain	387 (18.5)
Abdominal pain	315 (15.1)
Anemia	261 (12.5)
Dyspnea	206 (9.9)
Hypertension	199 (9.5)
Diabetes mellitus	195 (9.3)
Leukocytosis	182 (8.7)
Renal Failure	177 (8.5)
Vomiting	152 (7.3)
Nausea	150 (7.2)
Altered mental status	133 (6.4)
Fever	122 (5.8)
Cancer	109 (5.2)
Tachycardia	107 (5.1)
Hypotension	100 (4.8)
Lower urinary tract infection	97 (4.6)
Hypokalemia	96 (4.6)
Hyponatremia	92 (4.4)
Back pain	88 (4.2)
Syncope	88 (4.2)
Coronary artery disease	84 (4.0)
Pneumonia	81 (3.9)
COPD	78 (3.7)
CHF	76 (3.6)

Appendix E (continued)

GI bleed	75 (3.6)
Cellulitis	73 (3.5)
Headache	69 (3.3)
Alcohol abuse	69 (3.3)
Weakness	66 (3.2)
Others Diagnosis	325 (15.6)
Outside Information Types	
Outside medical records	1635 (77.9)
Outside laboratory results	389 (18.5)
Outside imaging results	382 (18.2)
Outside history and physical test results	255 (12.2)
Outside notes	206 (9.8)
Outside consultation	173 (8.2)
Outside discharge summary	164 (7.8)
Outside EKG results	153 (7.3)
Outside surgery or procedure notes	151 (7.2)

3.2. Association Rules

The final set of association rules is presented in Table 4. We fixed the minimum support at 2%, minimum confidence at 75%, lift values greater than 1, and the association rules had to have at least one health problem in the antecedent and one OI type in the consequent. Clinically relevant rules are presented in Table 4. A total of 20 association rules were found to be clinically relevant, of which the two with the lowest p-values (rules 3 and 16 in Table 4) do not satisfy $p < 0.01$. By the Benjamini-Hochberg correction method, we concluded that since $0.01 = (2/20)0.1$, these two results are not statistically significant at the corrected level $P < 0.1$. All of the rules were determined by chi square analysis and Benjamini-Hochberg correction not to be significant. Although our conservative approach resulted in no statistically sound association rules, there seems to be a trend between health problems and OI types for specific patient cohorts. For example, in terms of support, the stronger association rules found are {abdominal pain → outside medical records} and {anemia → outside medical records}. That is, outside medical records are frequently requested for abdominal pain and anemia patients with a support of 12% and 10%, respectively. When requesting OI for abdominal pain patients, there is an 83% confidence of requesting outside medical records. Similarly for anemia patients, there is an 80%

confidence of requesting outside medical records. The Internal Medicine Department usually serves people carrying several chronic conditions as comorbidities of an acute condition. Hence, most of the requests for outside medical records were for chronically ill patients. Despite this fact, the collected data show acute cases such as lower urinary tract infections typically trigger requests for outside medical records as well. For this particular patient cohort, there is an 86% chance of requesting outside medical records. Other acute conditions found among the 20 strong association rules were patients with abdominal pain, chest pain, nausea, and vomiting.

Table 4. The strong association rules between health problems and types of information requested during hospitalizations in the Internal Medicine Department of the Tampa General Hospital. Abbreviations: OMR, outside medical record; CHF, congestive heart failure; EKG, electrocardiogram; BH-FDR, Benjamini-Hochberg false discovery rate.

ID	Association Rules	Support	Confidence	Lift	N	χ^2	Uncorrected P-values	BH-FDR corrected p-values
1	Abdominal pain → OMR	12%	83%	1.06	261	0.57	0.55	0.10
2	Anemia → OMR	10%	80%	1.03	210	0.09	0.24	0.04
3	Dyspnea → OMR	8%	79%	1.01	163	0.01	0.06	0.01
4	Hypertension → OMR	8%	81%	1.04	162	0.10	0.25	0.05
5	Diabetes mellitus → OMR	8%	82%	1.04	159	0.10	0.25	0.05
6	Renal failure → OMR	7%	83%	1.06	147	0.18	0.33	0.07
7	Cancer → OMR	5%	88%	1.13	96	0.34	0.44	0.10
8	Lower urinary tract infection → OMR	4%	86%	1.09	83	0.12	0.27	0.03
9	Hypotension → OMR	4%	83%	1.06	83	0.05	0.18	0.06
10	Back pain → OMR	4%	85%	1.09	75	0.11	0.26	0.06
11	Pneumonia → OMR	3%	89%	1.14	72	0.18	0.32	0.01
12	Chest pain, Outside imaging	3%	93%	1.19	71	0.31	0.42	0.02

	→ OMR							
13	Anemia, Outside laboratory results → OMR	3%	93%	1.19	68	0.29	0.41	0.02
14	Abdominal pain, Nausea, OMR	3%	83%	1.06	63	0.03	0.14	0.03
15	Abdominal pain, Vomiting → OMR	3%	85%	1.09	63	0.07	0.20	0.04
16	CHF → OMR	3%	82%	1.04	62	0.01	0.09	0.07
17	Anemia, Outside imaging → OMR	3%	94%	1.20	58	0.28	0.40	0.08
18	Hypertension, Diabetes mellitus → OMR	3%	85%	1.09	57	0.06	0.19	0.09
19	Abdominal pain, Vomiting, Nausea → OMR	3%	85%	1.08	55	0.05	0.17	0.09
20	Chest pain, Outside EKG → OMR	2%	98%	1.25	48	0.23	0.37	0.08

4. DISCUSSION

We sought to uncover the relationship between the patients' health problems and the information needed from outside health care facilities in a large academic medical center. ARL was used to mine two and a half years of transactional data from the hospital EMR previous HIE implementation. Although previous investigations have made valuable contributions to the knowledge base on informational needs of physicians and patterns of use of HIE systems (e.g., [45,46]), most of them focus solely on hospital and primary care provider communication. We construct on these investigations considering the entire spectrum from which a hospital physician (i.e., hospitalist) may request patient records. With an increased number of handoffs between providers [47], due to the shift towards hospital medicine, studying informational needs of hospitalists becomes essential for improving HIE functionality, and thereby reducing barriers to adoption. We have also identified an important gap in the literature – most of the HIEs are built and implemented without first performing a user needs assessment. We believe HIE will be more successful if it is evaluated before, during and after implementation. To the best of our knowledge, there is no previous study serving as both needs assessment and baseline of informational needs prior to HIE implementation. Important to note is that hospitalists working in the department under study identified specific situations where they know outside information exists, but they do not request for records. For example, physician assumes the OI request process takes too long or the patient does not know where to request outside information from. These situations are amenable to HIE, therefore, physician OI request behavior may change after HIE implementation. We plan on capturing these variations in a future study.

Previous investigations suggest users have determined HIE is useful in some, but not all cases [40]. Our results indicate those patients hospitalized with chest pain were the target of outside information requests to obtain EKG results and other imaging test results. Other patient cohorts that were a common target of outside information requests were urinary tract infection patients and back pain patients. Indeed, Bailey and colleagues found HIE usage was associated with 64% lower odds of repeated imaging testing for back pain patients [6]. These findings can be translated into HIE design recommendations; for example, HIE systems should provide 1-click access to imaging, echocardiograms, bacterial cultures, cardiac catheterizations and CT scans allocated in other healthcare facilities for those patients with acute cardiac issues, urinary tract infection and back pain. Not only did our results indicate which patient populations are more prone to have outside records requested, they also indicated where future HIE research should focus to elucidate the value of information exchange among providers. Still, work lies ahead in elucidating whether or not streamlined access to outside information improves medical decision-making for other patient populations, and hence lower health care costs and improve patient outcomes. Future research should focus on determining the effects of having quick access to outside information in those patient cohorts previously unexplored; for example, urinary tract infection patients. Additionally, we would like to point out that few hospital transfers and physician referrals were included in our study. Since previous research found that incomplete patient records during transfers may lead to costly duplicated testing (e.g., [48]), future investigations should focus on the role of HIE during the admission of transferred patients.

A crucial step in improving information exchange between inpatient and other settings of care is the discharge summary [49–51]. Although The Joint Commission on Accreditation of Healthcare Organizations requires a discharge summary for every patient, usually, they do not provide timely and sufficient information for appropriate care transitions [52–54]. Kripalani and colleagues, in their 2007 systematic review of deficits in communication and information transfer between hospitalists and primary care physicians, infer that new health information technology and standardized methods of information exchange bears particular promise to improve care coordination [26,45]. Computer-generated summaries offer a quick way to present and highlight key elements of the hospitalization, and they are ready for delivery sooner than traditional summaries [55]. However, information needs and collection habits are not generic but instead vary among different types of physicians. Previous investigations found information needs and expectations of computers are influenced by specialty and practice setting [28,33,56,57]. Future research must determine differences between informational needs due to a variety of factors that include the young physician's lack of experience with fundamental clinical principles and the senior physician's lack of experience with information technology.

We found few other studies analyzing informational needs in the context of information exchange among healthcare organizations. Two studies, focused on the emergency department (ED) and outpatient care settings, found most OI users accessed patient summary data displayed by default in the HIE system followed by detailed laboratory and radiology information, which is consistent to what we found [58,59]. We contribute to this body of research by focusing on the inpatient care setting and hospitalists, who are key actors in coordinating the care of the patient within and outside the hospital. Ozkaynak and Brennan, during direct observation of ED workflows, found clinicians were more likely to request OI for admissions of chronic pain patients [60], which is consistent with our findings as well. However, during follow-up interviews, they found ED clinicians requested OI to identify drug seekers, which may not be the same motivation of hospitalists. Further research should explore hospitalists' perceptions on the value of OI to support medical decision-making.

There are important limitations to our work. First, we do not know if information-seeking efforts of hospitalists were successful. The collected transactional data have no information on whether or not the user located the desired information. Second, our study was restricted to a single hospital and thus a single EMR. However, most of the features of the in-use EMR were the same as the majority of hospitals across the nation. Third, the results of this work have limited generalizability in terms of the setting of care. Information users from other settings of care, even within the same hospital, may have different information needs. Yet, in the presence of data, our methodological approach can be reproduce to elucidate information needs in other clinical settings. Fourth, the usage of direct communication to verbally request OI (i.e., telephone call to the outside healthcare provider), which is then directly documented by the clinician in the patient's medical record were not included in this study. Finally, we did not address potential confounding due to region characteristics (e.g., the number of unaffiliated outside healthcare providers and their electronic medical record adoption rates).

5. CONCLUSION

We proposed a new approach to study informational needs of clinicians in the context of HIE. In particular, we uncovered the relationship between health problems and the most critical information requested, from outside health care facilities, in an internal medicine department of a tertiary care hospital. After data preparation, a set of disease-information association rules was built and then validated by clinical experts. This knowledge should inform the design and implementation of HIE in similar clinical settings, and in the presence of data, our approach can be used in other clinical settings as well. Our study contributes to fill the existing gap in knowing and understanding the clinical information needs in the context of new health information technology. With better knowledge of clinical information needs, it will become possible to conduct prospective studies of the clinical benefit of providing doctors with decision support tools that meet their outside information needs. Evidence can then be collected on whether improved access to outside information will result in more efficient or effective clinical decision-making or improved patient health outcomes. The effectiveness of health information exchange can thereby obtain its most eloquent validation.

6. CLINICAL RELEVANCE STATEMENT

Health information exchange is expected to facilitate a better delivery of care to patients. This study assists that goal by uncovering the most commonly requested clinical information from outside health care facilities by specific health problems. In the hands of HIE developers and implementers, our framework may facilitate screen redesign and enhanced record searching, and thereby reduce clinical workflow disruptions and troubles with the system interface.

7. CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest in this study.

8. HUMAN SUBJECTS PROTECTIONS

This study was performed in compliance with the World Medical Association Declaration of Helsinki on Ethical Principles for Medical Research Involving Human Subjects, and was reviewed by the Tampa General Hospital Office of Clinical Research and the University of South Florida (IRB # Pro00014574).

9. ACKNOWLEDGEMENTS

We thank Drs. Alexandra Strauss, Candice Mateja, and Stephanie Taylor for their valuable contributions in our study. We also thank Andres Garcia-Arce for his contributions during early stages of this project. Finally, we would also like to show our gratitude to the four anonymous reviewers for their comments that greatly improved our manuscript.

10. REFERENCES

1. Ward BW, Schiller JS, Goodman RA (2014) Multiple chronic conditions among US adults: a 2012 update. Prev Chronic Dis 11: E62. doi:10.5888/pcd11.130389.

2. Anderson G (2010) Chronic Conditions: Making the Case for Ongoing Care. Princeton, NJ.

3. Lucas DJ, Ejaz A, Haut ER, Spolverato G, Haider AH, Pawlik TM (2014) Interhospital transfer and adverse outcomes after general surgery: implications for pay for performance. J Am Coll Surg 218: 393–400. Available: http://www.ncbi.nlm.nih.gov/pubmed/24468232. Accessed 2 September 2014.

4. Kho AN, Lemmon L, Commiskey M, Wilson SJ, McDonald CJ (2008) Use of a Regional Health Information Exchange to Detect Crossover of Patients with MRSA between Urban Hospitals. J Am Med Informatics Assoc 15: 212–216. doi:10.1197/jamia.M2577.

Appendix E (continued)

5. Bailey JE, Wan JY, Mabry LM, Landy SH, Pope RA, Waters TM, Frisse ME (2013) Does health information exchange reduce unnecessary neuroimaging and improve quality of headache care in the emergency department? J Gen Intern Med 28: 176–183. Available: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3614141&tool=pmcentrez&rendertype=abstract. Accessed 16 January 2015.

6. Bailey JE, Pope R a, Elliott EC, Wan JY, Waters TM, Frisse ME (2013) Health Information Exchange Reduces Repeated Diagnostic Imaging for Back Pain. Ann Emerg Med. Available: http://www.ncbi.nlm.nih.gov/pubmed/23465552. Accessed 13 March 2013.

7. Unertl KM, Johnson KB, Lorenzi NM (2012) Health information exchange technology on the front lines of healthcare: workflow factors and patterns of use. J Am Med Inform Assoc 19: 392–400. Available: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3341790&tool=pmcentrez&rendertype=abstract. Accessed 10 September 2012.

8. Carr CM, Krywko DM, Moore HE, Saef SH (2012) The Impact of a Health Information Exchange on the Management of Patients in an Urban Academic Emergency Department: An Observational Study and Cost Analysis. Ann Emerg Med 60: S15. Available: http://dx.doi.org/10.1016/j.annemergmed.2012.06.062.

9. Vest JR, Miller TR (2011) The association between health information exchange and measures of patient satisfaction. Appl Clin Inform 2: 447–459. Available: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3612996&tool=pmcentrez&rendertype=abstract. Accessed 6 June 2013.

Appendix E (continued)

10. Solberg D, Roberts J (2009) “Pipe dream” HIE proves challenging. A community hospital network, concerned that each clinic’s needs could not be entirely met, decided on a standard EHR platform and a shared community network. Health Manag Technol 30: 22–23, 30.

11. Furukawa MF, King J, Patel V, Hsiao C-J, Adler-Milstein J, Jha AK (2014) Despite Substantial Progress In EHR Adoption, Health Information Exchange And Patient Engagement Remain Low In Office Settings. Health Aff (Millwood): hlthaff.2014.0445 – . Available: http://content.healthaffairs.org/content/early/2014/08/05/hlthaff.2014.0445.

12. Adler-Milstein J, Jha AK (2014) Health information exchange among U.S. hospitals: Who’s in, who's out, and why? Healthcare 2: 26–32. Available: http://www.sciencedirect.com/science/article/pii/S2213076414000025. Accessed 8 January 2015.

13. Rudin RS, Motala A, Goldzwelg CL, Shekelle PG (2014) Usage and Effect of Health Information Exchange: A Systematic Review. Ann Intern Med 161: 803–812.

14. Richardson JE, Abramson EL, Kaushal R (2012) The value of health information exchange. J Healthc Leadersh 4: 17–23.

15. Vest JR, Jasperson ’Jon Sean, Zhao H, Gamm LD, Ohsfeldt RL (2011) Use of a health information exchange system in the emergency care of children. BMC Med Inform Decis Mak 11: 78. Available: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3295672&tool=pmcentrez&rendertype=abstract. Accessed 10 September 2012.

Appendix E (continued)

16. Hincapie AL, Warholak TL, Murcko AC, Slack M, Malone DC (2011) Physicians' opinions of a health information exchange. J Am Med Inform Assoc 18: 60–65. doi:10.1136/jamia.2010.006502.

17. Kassirer JP (1998) Doctor discontent. N Engl J Med 339: 1543–1545. doi:10.1056/NEJM199811193392109.

18. Fischman J (2005) Whi will take care of you? Issues: 31.

19. Mechanic D (2003) Physician discontent: challenges and opportunities. JAMA 290: 941–946. doi:10.1001/jama.290.7.941.

20. Morrison I, Smith R (2000) Hamster health care. BMJ Br Med J 321: 1541–1542. doi:10.1136/bmj.321.7276.1541.

21. Morrison I (2000) The Future of Physicians' Time. Ann Intern Med 132: 80. Available: http://annals.org/article.aspx?doi=10.7326/0003-4819-132-1-200001040-00013.

22. Trude S (2003) So much to do, so little time: physician capacity constraints, 1997-2001. Track Rep: 1–4.

23. Sicotte C, Paré G (2010) Success in health information exchange projects: Solving the implementation puzzle. Soc Sci Med 70: 1159–1165. Available: https://www.healthypeople.gov/2020/topics-objectives/topic/health-communication-and-health-information-technology.

24. Karsh B-T (2009) Clinical Practice Improvement and Redesign: How Change in Workflow Can Be Supported by Clinical Decision Support: 1–34. Available:

Appendix E (continued)

http://www.nachc.com/client/Clinical Practice Improvement and Redesign_How Workflow can Support CDS.pdf.

25. Stead WW, Lin HS (2009) Computational Technology for Effective Health Care : Immediate Steps and Strategic Directions. Program 22: 121. Available: http://books.google.com/books?hl=en&lr=&id=HUAXQzIPxV8C&oi=fnd&pg=PT1&dq=Computational+teChnology+for+effeCtive+health+Care+immediate+StepS+a+n+d+StrategiC+direCtionS&ots=Sh4Pzoy3Fh&sig=P1WQnADNNPGkSeFLgy92VF4Ssv0.

26. Kripalani S, LeFevre F, Phillips CO, Williams M V, Basaviah P, Baker DW (2007) Deficits in communication and information transfer between hospital-based and primary care physicians: implications for patient safety and continuity of care. JAMA 297: 831–841. doi:10.1001/jama.297.8.831.

27. Stross JK, Harlan WR (1979) The dissemination of new medical information. JAMA 241: 2622–2624. doi:10.1001/jama.1979.03290500030017.

28. Strasser TC (2012) The information needs of practicing physicians in Northeastern New York State. J Med Libr Assoc 100: G. Available: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3571668&tool=pmcentrez&rendertype=abstract.

29. Curry L, Putnam RW (1981) Continuing medical education in Maritime Canada: The methods physicians use, would prefer and find most effective. Can Med Assoc J 124: 563–566.

Appendix E (continued)

30. Cohen SJ, Weinberger M, Mazzuca S a, McDonald CJ (1982) Perceived influence of different information sources on the decision-making of internal medicine house staff and faculty. Soc Sci Med 16: 1361–1364. doi:10.1016/0277-9536(82)90032-6.

31. Northup DE, Moore-West M, Skipper B, Teaf SR (1983) Characteristics of Clinical Information-Searching: Investigation Using Critical Incident Technique. J Med Educ 58: 873–881. Available: http://journals.lww.com/academicmedicine/Abstract/1983/11000/Characteristics_of_clinical_information_searching_.6.aspx.

32. Kochen M, Cohen L, Wulff Y (1985) Information systems and clinical research by residents in internal medicine. Methods Inf Med 24: 85–90.

33. Stinson ER, Mueller DA (1980) Survey of health professionals' information habits and needs. Conducted through personal interviews. JAMA 243: 140–143. doi:10.1001/jama.243.2.140.

34. Christensen DB, Wertheimer AI (1979) Sources of information and influence on new drug prescribing among physicians in an HMO. Soc Sci Med 13A: 313–322.

35. Covell DG, Uman GC, Manning PR (1985) Information needs in office practice: are they being met? Ann Intern Med 103: 596–599. doi:10.1059/0003-4819-103-4-596.

36. Rudin R, Volk L, Simon S, Bates D (2011) What Affects Clinicians' Usage of Health Information Exchange? Appl Clin Inform 2: 250–262. Available: /pmc/articles/mid/NIHMS335831/?report=abstract.

37. Abdullah U, Ahmad J, Ahmed A (2008) Analysis of effectiveness of apriori algorithm in medical billing data mining. Proceedings - 4th IEEE International Conference on

Emerging Technologies 2008, ICET 2008. pp. 327–331. doi:10.1109/ICET.2008.4777523.

38. Sharma N, Om H (2014) Extracting Significant Patterns for Oral Cancer Detection Using Apriori Algorithm. Intell Inf Manag 06: 30–37. Available: http://www.scirp.org/journal/PaperDownload.aspx?DOI=10.4236/iim.2014.62005.

39. Ilayaraja M, Meyyappan T (2013) Mining medical data to identify frequent diseases using Apriori algorithm. Proceedings of the 2013 International Conference on Pattern Recognition, Informatics and Mobile Engineering, PRIME 2013. pp. 194–199. doi:10.1109/ICPRIME.2013.6496471.

40. Vest JR, Zhao H, Jasperson J, Jaspserson J, Gamm LD, Ohsfeldt RL (2011) Factors motivating and affecting health information exchange usage. J Am Med Inform Assoc 18: 143–149. Available: http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3116259&tool=pmcentrez&rendertype=abstract. Accessed 1 August 2012.

41. Agrawal R, Imieliński T, Swami A (1993) Mining association rules between sets of items in large databases. ACM SIGMOD Rec 22: 207–216. doi:10.1145/170036.170072.

42. Hahsler M, Buchta BG, Hornik K (2015) Arules: Mining Association Rules and Frequent itemsts. Available: https://cran.r-project.org/web/packages/arules/index.html.

43. Alvarez SA (2003) Chi-squared computation for association rules: preliminary results. Chestnut Hill, MA.

44. Benjamini Y, Hochberg Y (1995) Controlling the false discovery rate: a practical and powerful approach to multiple testing. J R Stat Soc Ser B 57: 289–300.

Appendix E (continued)

45. Smith K (2014) Effective communication with primary care providers. Pediatr Clin North Am 61: 671–679. doi:10.1016/j.pcl.2014.04.004.

46. Koopman RJ, Steege LMB, Moore JL, Clarke MA, Canfield SM, Kim MS, Belden JL (2015) Physician Information Needs and Electronic Health Records (EHRs): Time to Reengineer the Clinic Note. J Am Board Fam Med 28: 316–323. Available: http://www.jabfm.org/cgi/doi/10.3122/jabfm.2015.03.140244.

47. Landrigan CP, Conway PH, Edwards S, Srivastava R (2006) Pediatric hospitalists: a systematic review of the literature. Pediatrics 117: 1736–1744. doi:10.1542/peds.2005-0609.

48. Stewart BA, Fernandes S, Rodriguez-Huertas E, Landzberg M (2010) A preliminary look at duplicate testing associated with lack of electronic health record interoperability for transferred patients. J Am Med Inform Assoc 17: 341–344. doi:10.1136/jamia.2009.001750.

49. Pantilat SZ, Lindenauer PK, Katz PP, Wachter RM (2001) Primary care physician attitudes regarding communication with hospitalists. Am J Med 111: 15–20. doi:10.1016/S0002-9343(01)00964-0.

50. Schabetsberger T, Ammenwerth E, Andreatta S, Gratl G, Haux R, Lechleitner G, Schindelwig K, Stark C, Vogl R, Wilhelmy I, Wozak F (2006) From a paper-based transmission of discharge summaries to electronic communication in health care regions. Int J Med Inform 75: 209–215. doi:10.1016/j.ijmedinf.2005.07.018.

51. Laye PG (1997) Tying up loose ends. Thermochim Acta 300: 237–245. doi:10.1016/S0040-6031(97)00076-2.

Appendix E (continued)

52. El-Kareh R, Roy C, Brodsky G, Perencevich M, Poon EG (2011) Incidence and predictors of microbiology results returning postdischarge and requiring follow-up. J Hosp Med 6: 291–296. doi:10.1002/jhm.895.

53. Roy CL, Poon EC, Karson AS, Ladak-Merchant Z, Johnson RE, Maviglia SM, Gandhi TK (2005) Patient safety concerns arising from test results that return after hospital discharge. Ann Intern Med 143: 121–128. doi:10.1016/j.athoracsur.2010.09.032.

54. Walz SE, Smith M, Cox E, Sattin J, Kind AJH (2011) Pending laboratory tests and the hospital discharge summary in patients discharged to sub-acute care. J Gen Intern Med 26: 393–398. doi:10.1007/s11606-010-1583-7.

55. Van Walraven C, Laupacis A, Seth R, Wells G (1999) Dictated versus database-generated discharge summaries: A randomized clinical trial. Cmaj 160: 319–326.

56. Teach RL, Shortliffe EH (1981) An analysis of physician attitudes regarding computer-based clinical consultation systems. Comput Biomed Res 14: 542–558. doi:10.1016/0010-4809(81)90012-4.

57. Singer J, Sacks HS, Lucente F, Chalmers TC (1983) Physician attitudes toward applications of computer data base systems. JAMA 249: 1610–1614. doi:10.1001/jama.1983.03330360050035.

58. Campion TR, Edwards AM, Johnson SB, Kaushal R (2013) Health information exchange system usage patterns in three communities: practice sites, users, patients, and data. Int J Med Inform 82: 810–820. Available: http://www.sciencedirect.com/science/article/pii/S1386505613001056. Accessed 28 November 2014.

Appendix E (continued)

59. Johnson KB, Unertl KM, Chen Q, Lorenzi NM, Nian H, Bailey J, Frisse M (2011) Health information exchange usage in emergency departments and clinics: the who, what, and why. J Am Med Inform Assoc 18: 690–697. doi:10.1136/amiajnl-2011-000308.

60. Ozkaynak M, Brennan PF (2012) Revisiting sociotechnical systems in a case of unreported use of health information exchange system in three hospital emergency departments. J Eval Clin Pract: 1–4. Available: http://www.ncbi.nlm.nih.gov/pubmed/22420774. Accessed 27 September 2012.

Appendix F: A Strategic Gaming Model for Health Information Exchange Markets

Appendix F presents the manuscript titled, "A Strategic Gaming Model for Health Information Exchange Markets", which is under review in the Journal of the American Medical Informatics Association.

Appendix F (continued)

A STRATEGIC GAMING MODEL FOR HEALTH INFORMATION EXCHANGE MARKETS

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Preprint submitted to the Journal of the American Medical Informatics Association

ABSTRACT

Objective: To describe a mathematical model for estimating the willingness of health care organizations to adopt HIE under different scenarios of federal incentives and health information blocking, and to demonstrate its use in HIE policy design.

Methods: We built a bi-level integer program (BiIP), in which the upper-level emulates the hospital decision of adopting HIE, and the lower-level emulates the patient decision of switching hospital. Multi-hospital Nash equilibria, in which each hospital solves the BiIP, are calculated and interpreted as the willingness of a hospital to adopt HIE based on its competitors decision. We applied our model to 1,093,177 patient encounters over a 7.5-year period in nine hospitals geographically located within three adjacent counties in Tampa, Florida.

Results: For this community and under a particular set of assumptions, hospitals may set HIE adoption decisions to threaten the value of HIE even with federal monetary incentives in place. Medium-sized hospitals are more reticent to adopt HIE compared to large-sized institutions. Collusions to not join HIE significantly reduce the effectiveness of current and proposed federal incentive structures.

Discussion: Although health information blocking is commonly attributed to health IT developers, health care providers may also become a significant barrier for nationwide HIE. Smaller hospitals are more reticent to HIE, which may be attributed to market share loses and limited HIE adoption budgets and health IT infrastructure. Competition between hospitals coupled with volume-based payment systems create no incentives for smaller hospitals to exchange their data with competitors.

Conclusion: Our model can be used by policy makers to find incentive structures that will spur HIE participation in a given community. Although the recent shift from volume- to value-based medicine may amplify the benefits of HIE for providers, medium-sized hospitals need targeted actions to mitigate market incentives to not adopt HIE.

1. BACKGROUND AND SIGNIFICANCE

Over the next 10 years, it is expected that all health care organizations in the United States be able to exchange electronic patient data through health information exchange (HIE) with affiliated and unaffiliated organizations. From the late 1990s, relevant stakeholders and the research community have recommended that all electronic medical record systems (EMR) be interoperable to facilitate care coordination and cost savings.[1,2] The federal government has taken an active role to stimulate such interconnectivity. Enacted in 2009, the Health Information Technology for Economic and Clinical Health (HITECH) Act has been providing a base incentive of $2,000,000 for those hospitals electronically exchanging patient information with unaffiliated providers. Although recent evidence shows mixed results about the positive impact of HIE, two recent systematic reviews suggest it may be due to a lack of widespread HIE adoption.[3,4] There has been an uptick in HIE adoption since the enactment of the HITECH Act, however only 30% of hospitals and 14% of solo practices are conducting HIE activities with significant state-to-state variations.[5,6] Common barriers to HIE adoption include interface and workflow issues, privacy and security concerns of patient data, and the financial sustainability of organizations facilitating information exchange.[7–11] A less studied but equally important barrier is the strategic role of “owning” patient information.

A recent report from the Office of the National Coordinator for Health Information Technology (ONC) establishes that current market conditions create incentives for some entities to exercise control over patient data in ways that unreasonably limit its availability and use.[12]

This issue, named *health information blocking*, is used as a mean of locking-in patients to enhance market share and reinforce market dominance of established entities. Empirical and modeling studies on HIE capabilities and trends provide the necessary context for understanding the nature and extent of health information blocking. Recent evidence shows that large for-profit hospitals are less likely to adopt HIE compared to non-profit hospitals and hospitals with no significant market share or with operations in less concentrated markets.[5] Another study found large health systems more likely to exchange electronic patient data internally but are less likely to exchange with competitors and unaffiliated providers.[13] Although providers are legally required to share patients' records, there is also anecdotal evidence that providers are hesitant to release records to patients transferring to other providers.[12,14–17] Hospital administration have outlined concerns about losing competitive advantages by ceding full control of "their" data.[18] While the evidence is limited, there is little doubt that health information blocking is occurring and is interfering with nationwide HIE.

Various modeling studies on HIE have been undertaken to study HIE network structure and financial sustainability.[36–42] However, only a few have focused on issues related to health information blocking and the strategic decision of adopting HIE. Zhu and colleagues proposed a game theoretic approach to studying the strategic behavior of data owners and HIE adoption.[43] Desai developed a game theoretical model to analyze the potential loss of competitive advantage due to HIE adoption.[20] A crucial difference among these studies on health information blocking is the type of interaction assumed between hospitals and patients, and among competing hospitals. In hospital competition focused models, hospital interactions can be summarized in terms of conjectural variation (i.e., each hospital's decision to adopt HIE is predicated on the way it perceives its competitors may react). The proposed model, unlike previous approaches, calculate oligopolistic equilibriums of HIE adoption using the hospital utility function conjectural variations while considering the discrete range patients' options of where to purchase health care services. The resulting bi-level mathematical program can be used to deepen our understanding of health information blocking under different market structures. More importantly, policy makers can use our model to answer the fundamental question of, *what should be the optimal levels of federal incentives that will spur HIE adoption across United States?*

2. OBJECTIVE

There is a need of stronger and targeted policy that stimulates competing health care organizations to adopt HIE. Our objective is to describe a mathematical model for estimating the willingness of health care organizations to adopt HIE, which considers different levels of federal incentive structures and health information blocking.

3. MATHERIAL AND METHODS

3.1. Market assumptions

In our model, we establish a finite number of hospitals serving a finite number of patients. Hospitals decide whether or not to adopt HIE. The patient then decides whether or not to switch the hospital where they consume health care services based upon an extension of the utility function used in [20]. By not adopting HIE, hospitals may be able to increase their patient volume and profit by reducing patient migration to other hospitals. Alternatively, by adopting HIE, hospitals may increase volume and profit by treating patients migrating from other hospitals and by receiving marginal benefits of joining an HIE network. In a community served by a multi-hospital system, a Nash equilibrium will occur when no hospital has any incentive to unilaterally change its HIE adoption decision. The model presented in [20] is similar to ours, except for two differences. The first difference is that in [20] a duopoly market is assumed—the multi-hospital equilibriums are not calculated neither discussed. We instead consider reactions of more than two competing hospitals in a given community, which we argue is a more realistic representation of HIE markets. Second, our model are constrained by hospital HIE adoption budgets and by patient allocation needs, i.e., patients in our model have specific care needs that cannot be served by every hospital (see Section 3.3 for further details).

In this model, we assume all hospitals are for-profit institutions maximizing expected payoffs. The hospitals have a designated budget for HIE implementation, and must not run a budget deficit. We assume only the hospitals manipulate the decision to adopt HIE. On the other hand, patients are considered to maximize their utilities, which are measured in terms of the quality of care offered by each hospital, the personal preference each patient has for each hospital, and the switching costs generated at the time of moving health information from one health care provider to another one. We assume all patients purchase medical insurance, and thereby they are insensitive to price changes on health care services.[21] The timing of the model timing is as follows. First, patients are randomly assigned to a hospital (index hospital) with imperfect information about their personal hospital preference. Second, patients learn their hospital preference perfectly, and we assume the prospect of the hospital adopting HIE causes no impact on the patient's utility function. Third, hospitals decide whether or not to adopt HIE. Finally, patients decide whether or not to switch the index hospital. If the index hospital decides to adopt HIE, then the switching costs for the patient are reduced to zero. We also assume that patient switching costs are reduced to zero even if only the index hospital decides to adopt HIE.

We have developed two utility-based models representing the interactions of hospitals and patients in a health care delivery market in the context of HIE. The bi-level model can be phrased as follows. There are some dominant hospitals in the market, each deciding whether or not to adopt HIE. The model tries to determine the optimal HIE adoption decision for each hospital. Hospitals can be thought of as a leader of a Stackelberg game, and the leader calculates its decision based on anticipating what the patients in a given community would do.

The patients' assumed reactions are based on their utility functions and are considered by solving one integer program representing the patient's purchase decision.

3.2. Mathematical formulation

Mathematically, the HIE market can be formulated as an oligopolistic market equilibrium model on a network consisting of the node sets I and J, where the set I corresponds to the hospitals in a given community and the set J corresponds to the patients served by the multi-hospital network. There are several hospitals in the market, each serving specific members of the population. In this section, we give the precise formulation of the single-hospital problem, and the solution strategy for a multi-hospital problem.

3.3. The single-hospital problem

In essence, the single-hospital problem is a two-level constrained optimization problem in which a hospital takes as inputs its perceived market conditions (including any competitors' service and demand functions) and maximizes profit under a set of equilibrium constraints. In the terminology of a bi-level optimization problem, the upper-level variables consist of the hospital's decision to adopt HIE and the lower-level is the patient's decision as to switch hospital. The upper-level problem is parameterized by the patient's willingness to switch which is restricted by given bounds; such bounds constitute the upper-level constraints. The upper-level objective is the hospital's profit, equal to its revenues less its costs.

The single-hospital problem focuses on a hospital denoted by $i^* \in I$. The following is the notation used in the formulation of this problem.

Sets:

I Set of all hospitals

Appendix F (continued)

J Set of all patients

T_j Set of all hospitals where patient j cannot purchase health care services

Indices:

i Hospital in the network

j Patient in the network

Parameters:

α A scalar

v_i Vertical quality component for hospital i

r_{ij} Personal preference for hospital i by patient j

s Switching cost

p Price of service

q_i Number of patients served by hospital i

f_i Quantity of federal monetary incentive for adopting HIE

β_i Marginal benefit per patient a hospital i receives from HIE

C_{HIE} Fixed HIE adoption cost

B_i Budget allocated by hospital i for HIE adoption

Lower-level patient decision variables:

t_{ij} 1 if patient j consumes from hospital i and 0 otherwise

y_{ij} 1 if patient j migrates from hospital i and 0 otherwise

Upper-level hospital decision variables:

e_i 1 if hospital i adopts HIE and 0 otherwise

Appendix F (continued)

The lower-level patient switching problem is formally stated as the following mathematical program in variable t_{ij} and y_{ij}, parametrized by decision e_i for $i \in I$.

- Maximization of patient's payoff

$$\max_{t_{ij}, y_{ij} \in \{0,1\}^2} \sum_i \sum_j t_{ij} \left[\alpha \left(v_i + r_{ij} \right) - (1 - e_i) s \right] \quad (1)$$

- constrained by the set of hospitals to which a patient cannot migrate due to special health care needs: for all patients $j \in J$,

$$\sum_{i \in T_j} t_{ij} = 0 \quad (2)$$

- by the migration of a patient to a unique hospital: for all patients $j \in J$,

$$\sum_{i \neq i^*} t_{ij} = y_{i^* j} \quad (3)$$

- and, by the binary decision variables

$$t_{ij}, y_{ij} \in \{0,1\}^2 \quad (4)$$

With the lower-level problem defined, we may now complete the upper-level problem that hospital $i^* \in I$ solves to determine its decision of adopting HIE. Specifically, taking t_{ij} and y_{ij} for all $j \in J$ as given, hospital $i^* \in I$ maximizes its payoff.

- Maximization of hospital's profit

$$\max_{e_i \in \{0,1\}} p \left[q_{i^*} + \sum_j t_{i^* j} - \sum_j y_{i^* j} \right] + e_i \left[\beta_i \left(q_{i^*} + \sum_j t_{i^* j} - \sum_j y_{i^* j} \right) - C_{HIE} + f_i \right] \quad (5)$$

- constrained by the budget that each hospital allocates for HIE adoption: for all hospitals $i \in I$,

$$e_i[C_{HIE} - f_i] \le B_i \tag{6}$$

- and by the binary decision variables

$$e_i \in \{0,1\}. \tag{7}$$

Rewriting the resulting formulation (1) – (7), we obtain the following bi-level integer program, to which we refer as BiIP. The upper-level of problem (8) represents the interest of hospital $i \in I$, while the lower-level represents the interest of patient $j \in J$. The hospital is classified as leader of the bi-level program, and the patients are classified as followers.

BiIP:

$$\begin{aligned}
&\max_{e_i \in \{0,1\}} p\left[q_{i^*} + \sum_j t_{i^*j} - \sum_j y_{i^*j}\right] \\
&\qquad\qquad + e_i\left[\beta_i\left(q_{i^*} + \sum_j t_{i^*j} - \sum_j y_{i^*j}\right) - C_{HIE} + f_i\right] \\
&\qquad\qquad subject\ to\ e_i[C_{HIE} - f_i] \le B_i, \forall i, \\
&\qquad\qquad\qquad e_i \in \{0,1\}, \\
&(t_{i^*j}, y_{i^*j}) \in \max_{t_{ij}, y_{ij} \in \{0,1\}^2} \left\{\begin{matrix} \sum_i \sum_j t_{ij}\left[\alpha\left(v_i + r_{ij}\right) - (1 - e_i)s\right]: \\ \sum_{i \in T_j} t_{ij} = 0, \forall j, \sum_{i \ne i^*} t_{ij} = y_{i^*j}, \forall j, \\ t_{ij}, y_{ij} \in \{0,1\}^2 \end{matrix}\right\}.
\end{aligned} \tag{8}$$

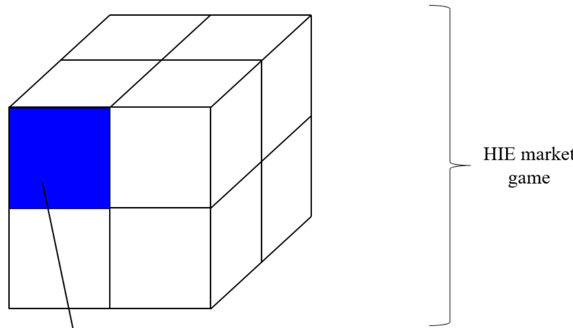
3.4. Solution strategy for the single and multi-hospital problem

Bi-level optimization models have been widely used to study strategic behavior of market participants in different markets.[22–24] Bi-level models include two mathematical programs, where one serves as a constraint on the other. For a lower level model, with convex and feasible space and objective function, the first order necessary conditions represent a solution for the model.[25] The model presented in Section 3.3 does not comply with these assumptions since the lower-level model is a non-convex model due to the presence of integer decision variables. A number of solution approaches have been discussed to tackle problems of this type. However, most of these approaches do not necessarily guarantee a solution to be optimal,[26] and if they do, computational requirements are cost prohibitive for large problems as the one under study.[27]

To guarantee that an optimal solution is obtained for the bi-level formulation presented in Section 3.3, the bi-level model is solved in two steps. First, we fixed the hospital's decision of whether to adopt ($e_i = 1$) or not ($e_i = 0$) HIE; after that, given the hospital's decision, the lower level model becomes a single level mixed integer problem, which can be solved independently. Once the lower level model is solved for both each possible value of e_i, the optimal solution for hospital $i \in I$ can be obtained by choosing the maximum between $F(e_i = 1)$ and $F(e_i = 0)$, where $F(e_i)$ represents the profit of hospital $i \in I$.

When multiple hospitals participate in the HIE market, the equilibrium strategies among those hospitals need to be obtained. In this context, each hospital faces and needs to solve the bi-level model. Since the bi-level solution approach considers testing each possible hospital strategy, the game and the corresponding market equilibrium can be formulated as a matrix game. Each position in the matrix game represents the profit of each hospital for a unique combination of strategies $E(e_1, e_2, e_3, \dots, e_i)$. The representation of the matrix game and solution approach for obtaining the market equilibrium is presented in Figure 1.

Appendix F (continued)



$$(t_{i^*j}, y_{i^*j}) \in \max_{t_{ij}, y_{ij} \in \{0,1\}^2} \left\{ \begin{array}{c} \sum_i \sum_j t_{ij}\left[\alpha(v_i + r_{ij}) - (1-e_i)s\right] : \\ \sum_{i\in T_j} t_{ij} = 0, \forall j, \sum_{i \neq i^*} t_{ij} = y_{i^*j}, \forall j, \\ t_{ij}, y_{ij} \in \{0,1\}^2 \end{array} \right\} \text{Patients problem}$$

Figure 1. Diagram of the solution approach for obtaining market equilibrium in a multi-hospital problem. Abbreviations: HIE, health information exchange.

As stated earlier, each position in the matrix game represents a combination of strategies $E(e_1, e_2, e_3, \ldots, e_i)$ of the hospitals. In order to obtain an equilibrium, we evaluate each combination of these strategies in the lower-level problem and calculate the profit for each hospital according to the hospital's objective function described in section 3.3. Once each possible strategy combination in the matrix is populated with the corresponding hospitals' profits, the equilibrium can be obtained. A strategy profile $E^*(e_1^*, e_2^*, e_3^*, \ldots, e_i^*)$ is a Nash equilibrium (NE) if no unilateral deviation in strategy by any single player is profitable for that player. That is, the strategy $E^*(e_1^*, e_2^*, e_3^*, \ldots e_i^*)$ is said to be a NE if:

$$\forall i \in I, F_i(e_i^*, e_{-i}^*) \geq F_i(e_i, e_{-i}^*)$$

If a pure NE cannot be found, a mixed strategy NE can be always found based as proven by [28]. A mixed strategy NE assigns a probability distribution to the set of strategies that hospitals can take. The probability distribution is understood in our context as the willingness of hospitals to join and HIE network.

4. RESULTS

We now illustrate how the proposed model can assist the analysis of HIE markets and development of HIE policy. Using a sample hospital network, the model can be used to assess HIE adoption levels in a given region under various scenarios of federal monetary incentives, as well as different levels of health information blocking (i.e., collusions to avoid HIE adoption). We conduct three numerical studies to answer the following questions: 1) How will HIE adoption rates be affected by federal incentives? 2) How will HIE adoption be affected by market power? 3) What degree of market power results in significant market inefficiencies that should be mitigated? To answer the first question, we evaluated a set of existing federal incentive structures and a set of proposed penalties. To answer the second and third questions, we simulated collusions by randomly assigning a subset of hospitals to not adopt HIE. In our model, the number of hospitals in the fictitious collusions varies as in the following levels: *none*, no hospitals colluded; *minor*, two hospitals colluded; *moderate*, four hospitals colluded; *severe*, six hospitals colluded; and *extreme*, eight hospitals colluded. We then evaluated the impact of the collusion level on the other hospitals' willingness to engage in HIE. We also use the *moderate* collusion scenario for evaluating a number of ad-hoc incentive structures that vary within current incentives and proposed penalties. These experiments allow a deeper understanding of the effectiveness of existing and proposed actions to promote HIE adoption.

4.1. Sample hospital network and model validation

For the numerical studies proposed above, patient flow data were collected from administrative claims of nine hospitals geographically located within three adjacent counties in Tampa, Florida. Hospitals with 88-218 beds were classified as *medium-sized* and those with more than 218 beds as *large-sized*. The dataset includes 1,093,177 patient encounters (594,751 unique patients) from January 2005 to July 2012. The vertical quality component of each hospital, v_i,

Appendix F (continued)

and the patients' personal preferences, r_{ij}, are randomly generated in the interval [0,1]. The switching cost is assumed to be $50, and the average price of service is set to $9,700 as presented in [29]. To be conservative, the marginal benefit per patient a hospital i receives from HIE are set to 60-70% of the values presented in [30] of $26 per admission, so at least we account for HIE benefits in those encounters initialized through the emergency departments. The federal monetary incentives given to each hospital for HIE adoption are up to $2,000,000. [31] Since evidence on the costs of HIE adoption are scarce, we set HIE adoption cost at $900,000 based on anecdotal evidence. [32] Finally, the HIE adoption budget of each hospital i is randomly generated in the interval [800000, 1000000]. Hospital network characteristics and model parameters are summarized in Table 1.

Table 1. Hospital network characteristics and model parameters. Medium-sized hospital, 88-218 beds; large-sized hospital, >218 beds.

	Hospital								
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Size	Large	Medium	Large	Medium	Large	Medium	Medium	Large	Medium
Average patient volume per year [patients]	4,013	2,162	7,830	1,205	3,425	1,759	2,358	7,813	1,106
α [$]	150								
v_i	$unif(0,1)$								
r_{ij}	$unif(0,1)$								
s [$]	50								
p [$]	9,700								
f_i [$]	2,000,000								
β_i [$]	15.36	16.5	13.86	16.47	19.72	13.2	16.12	15.18	16.47
C_{HIE} [$]	900,000								
B_i [$]	882,107	846,300	796,943	731,111	796,010	856,995	852,583	840,047	863,011

To validate the model, we compared the actual versus simulated average patient volume. The vertical quality components for each hospital, v_i, were manipulated within the [0, 1] interval until divergences from the actual patient volume were lower than 5% (see Table 2).

Table 2. Model calibration results.

	Hospital								
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Actual average patient volume per year [patients]	4,013	2,162	7,830	1,205	3,425	1,759	2,358	7,813	1,106
Simulated average patient volume, q_i [patients]	4,072	2,221	8,203	1,230	3,528	1,782	2,465	8,063	1,107
Estimated vertical quality component, v_i	0.810	0.735	0.925	0.680	0.790	0.715	0.75	0.92	0.675
Error [%]	1.5	2.7	4.8	2.1	3.0	1.3	4.5	3.2	0.1

4.2. Market and policy analysis

The BiIP model was implemented in GAMS and solved using CPLEX.[33] The multi-hospital Nash equilibrium search was performed using the algorithm presented in [34] and implemented in MATLAB.[35] Numerical studies are presented next to illustrate the usefulness of the proposed model.

4.3. How will HIE adoption rates be affected by federal incentives?

To investigate the impact of federal incentives on HIE adoption in the community under study, we calculated multi-hospital Nash equilibrium under scenarios of penalties of up to $2,000,000 for those hospitals not joining HIE and incentives of up to $2,000,000 for those hospitals joining HIE. As presented in Figure 2, we found higher sensitivity to penalties than incentives. We also found that not always a greater incentive (or penalty) is the most effective strategy to promote HIE adoption. For example, our results suggest that a penalty of $500,000 is more effective than a penalty of $1,000,000 to generate significant engagement of the hospitals in the community under study. To investigate these patterns further, we compared the behavior of medium-sized versus large-sized hospitals. In Figure 3, we can see medium-sized hospitals reticent to adopt HIE. Possible explanations of such behavior are that medium-sized hospitals are more afraid of losing significant market share due to patient migration or that they are limited by HIE adoption budgets and health IT infrastructure. These results are aligned with empirical evidence suggesting that large hospital systems are more likely to have greater HIE capabilities than small and single practice providers. [13] In summary, under a particular set of assumptions, hospitals set HIE adoption decisions to threaten the value of HIE even with federal monetary incentive structures in place.

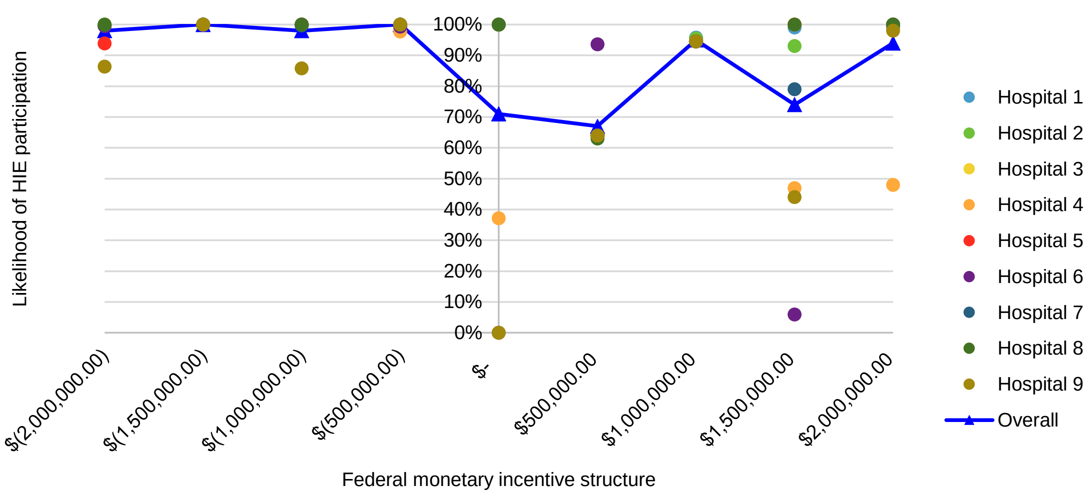


Figure 2. Influence of federal monetary incentive structures on promoting HIE engagement in a community served by nine hospitals. Abbreviations: HIE, health information exchange

Appendix F (continued)

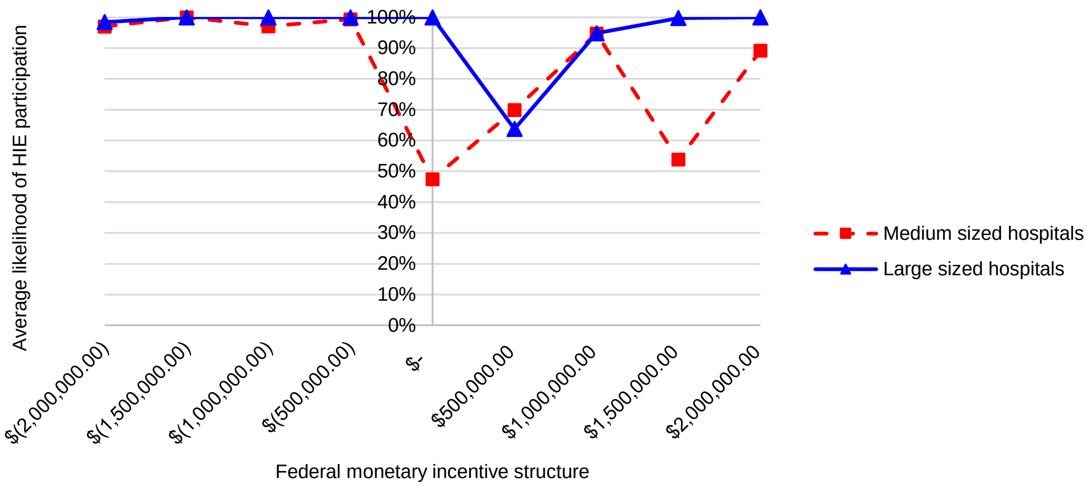


Figure 3. Influence of federal monetary incentive structure on promoting HIE engagement in a community served by five medium-sized hospitals and four large-sized hospitals. Abbreviations: HIE, health information exchange.

4.4. Influence of federal monetary incentives on promoting HIE adoption in a community suffering health information blocking

We now address the following fundamental questions, how will HIE adoption be affected by health information blocking? What degree of health information blocking results in significant market inefficiencies that should be mitigated? To investigate further the issue of health information blocking, we use our model to simulate collusions among a subset of hospitals to not join HIE, and then evaluate the impact of these collusions on HIE adoption. Collusions are an agreement between two or more market participants to limit open competition and thereby gaining an unfair market advantage. In the context of HIE, most stakeholders are committed to achieve nationwide interconnectivity, but current economic and market conditions create business incentives for some market participants to exercise unreasonable control over patient data. Practices of health information blocking include, among others, providers implementing health IT in non-standard ways that are likely to increase the costs and complexity of electronic exchange of health information. Providers may collude to not join HIE as a means to control referrals and enhance their market dominance. As presented in Figure 4, we found that moderate collusions to not join HIE reduce the effectiveness of current (and proposed) federal incentive structures. Although health information blocking complaints are frequently attributed to health IT developers, we found health care providers may also become a significant barrier for nationwide interconnectivity.

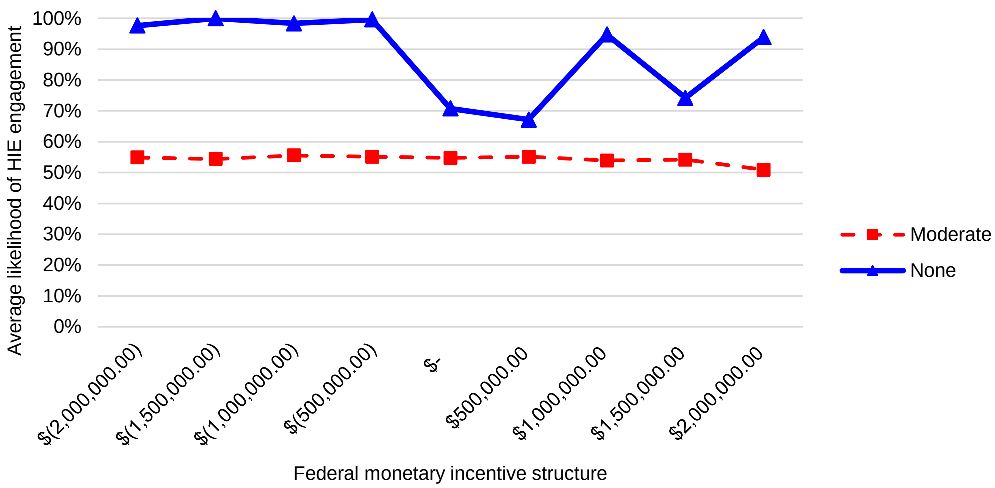


Figure 4. Influence of federal monetary incentive structures on promoting HIE engagement in a community with health information blocking. To simulate the moderate collusion scenario, two medium-sized (2 & 4) and two large-sized (3 & 8) hospitals were randomly selected and forced not to adopt HIE. Abbreviations: HIE, health information exchange.

DISCUSSION

The intent of the HITECH Act was to drive the rapid adoption of interoperable EMRs to support care and efficiency improvements in the United States health care system. While the intent was and is clear to the majority of stakeholders, some entities are knowingly interfering with electronic information exchange across disparate and unaffiliated providers to gain market advantage. We propose a strategic gaming model for assessing health care provider decision to adopt HIE, which simulates an oligopolistic health care delivery market consisting of several dominant hospitals. In our model, the interactions between hospitals and patients are modeled as a Stackelberg game, in which the hospital is the leader, and the patient is the follower. Each patient decides whether or not to switch the hospital where they consume health care services based upon an extension of the utility function presented in [20], which includes personal preferences, perceived hospital quality, and switching costs. As reported in [12], switching costs may arise when there exists: 1) contract terms, policies or other business practices that restrict individuals' access to their electronic health information, 2) fees for data exchange among providers, and 3) non-standard health IT technologies that increase the costs and complexity electronic exchange of patient information. We assume that patient switching costs are reduced to zero when a hospital adopts HIE. Therefore, hospitals not adopting HIE may exercise health information blocking to increase their profit by reducing patient migration.

A deeper understanding of the role of health information blocking and federal incentives to promote HIE adoption can help modify and improve current HIE policy. With the increasing evidence supporting the effect of HIE use on reduced utilization and costs in emergency departments,[3] there is the need for policies and incentives to stimulate competing organizations to freely share patient data electronically and minimize health information blocking. There are several ways to explore, understand, and anticipate the effects of new HIE policy. First, ex-post analysis of current markets to empirically determine whether or not hospitals are engaged in HIE (e.g., [6]) Second, ex-ante analysis of market concentration using the Herfindahl-Hirschman Index (e.g., [19]), which focuses on hospital market share and ignores HIE adoption costs and health information blocking. Third, ex-ante experimental analysis investigating interactions of HIE market structures and participant behavior. However, they often involve naïve subjects and their associated cost makes replication, sensitivity analysis, and generalization to other circumstances limited. Last, ex-ante modeling analysis using artificial subjects is capable of integrating HIE adoption incentives, blocking behaviors, and market share - all factors that affect HIE adoption. These types of models allow us to calculate HIE adoption levels in a given region, and are more easily generalized and analyzed for sensitivity.

When evaluating the behavior of hospitals under no incentive structures, our model suggest that in the community under study six out of nine hospitals had market incentives to adopt HIE–the three hospitals not willing to adopt HIE were medium-sized hospitals. Market incentives to adopt HIE were driven by direct benefits of adopting HIE, such as reductions of repeated testing and reduction of hospital readmissions, as well as market share gains facilitated by HIE. In a meta-analysis published in 2012, Fareed found that large hospitals have lower mortality rates than smaller hospitals, and therefore patients may have incentives to switch from medium- to large-sized hospitals. Such market incentives, combined with HIE's potential on lowering patient switching costs,[44] may be perceived by smaller hospitals as a threat for market share and thereby a barrier to adopting HIE. Competition between hospitals coupled with volume-based payment systems create no incentives for smaller hospitals to exchange their data with competitors because they want to keep lucrative services within their hospital.[45–48] Although we believe the recent shift from volume- to value-based medicine will only amplify the benefits of HIE adoption across all providers, medium-sized hospitals may need targeted actions to mitigate market incentives to not adopt HIE.

In a recent report to the Congress,[12] the ONC recognizes health information blocking as an important and unexplored barrier for HIE adoption. In order to deepen our understanding about health information blocking, we used our proposed model to analyze the effect of a collusion between two or more hospitals to not join HIE. Our model suggest that health care provider health information blocking is a significant barrier for nationwide interconnectivity.

Appendix F (continued)

Moreover, current monetary incentives, as well as proposed penalties, had little or no effect on stimulating HIE adoption in the community under study. Our results highlight the need for a new and comprehensive strategy to remedy health information blocking. Current federal monetary incentives are not enough to reach nationwide HIE. Although a common practice of providers is to justify not adopting HIE due to privacy and data security concerns, there are reports of privacy laws being cited in situations in which they do not in fact impose restrictions. The Health Insurance Portability and Accountability Act (HIPAA), enacted in 1996, does not restrict patient data from being shared between providers. The HIPAA Privacy Rule only establishes national standards of privacy protections and rights, which applies to health plans, health care clearinghouses, and providers. The Rule requires appropriate safeguards to protect the privacy of personal health information, as well as setting limits and conditions on the uses and disclosures that may be made of such information without patient authorization. In other words, as long as patient consent is obtained, no further restrictions are imposed by HIPAA in a patient information transaction between providers.

In the same report, ONC proposes to strengthen the regulatory environment that is conducive to the exchange of electronic health information. More precisely, ONC seeks to work with CMS to coordinate payment incentives and leverage other market drivers to reward interoperability and exchange, and to discourage health information blocking. Among several policy layers that are under discussion, new incentives to adopt HIE and penalties that raise the costs of not moving to interoperable health IT systems were proposed by ONC. In light of these debates, under particular market assumptions, our results suggest that penalties may be more effective than incentives to promote HIE adoption in the particular community under study. Still abundant research is needed to estimate the optimal design of proposed penalties.

Study limitations and future research are discussed next. First, our research does not considers the physician opinion or willingness to use electronical medical records (EMR). Rather, the model decides from a net economic perspective. Therefore, we cannot assess the influence of individual, organizational, and contextual factors on hospital adoption of HIE. Second, our NE search method does not provides the one and unique equilibrium of a game. Instead, the method finds the one equilibrium out of many a game may have that is best in the sense that all players have optimized their payoffs/utilities rather than adjusted to their beliefs about other players in the game. Third, although out of the scope of this investigation, health information blocking behavior can also be generated by health IT developers (i.e., EMR vendor competition), or by coordinated actions between developers and their health care provider customers. For instance, developers charge fees that make it cost-prohibitive for providers to engage in HIE with other providers using a competitor EMR system. Future work will study the role of competition in the health IT developers market, and how their actors behave under different market structures.

CONCLUSION

A practical and efficient bi-level model for calculating oligopolistic HIE participation equilibrium in health care provider markets has been developed and illustrated. The equilibrium is a mixed strategy Nash equilibria interpreted as the willingness of each health care provider to share freely data with other providers. An important barrier for reaching interoperability of EMR systems is the strategic role of “owning” patient information that providers may lose by joining HIE. The existing evidence, containing both empirical and modeling studies, helps to support the design of HIE networks and to assess the potential impact of HIE policies. Our research extends the existing evidence by incorporating the strategic behavior providers have at the time of deciding whether or not to adopt HIE. This type of behavior and interaction can be illustrated in terms of a health care provider’s conjectural variation–what does each hospital assume about its competitors' responses to its actions? The proposed model allows for deeper understanding of why hospitals do not engage in HIE and the circumstances in which they do. Using sample data from hospitals in Florida, we studied the potential impact of current and proposed HIE policy, as well as the impact of health information blocking in the level of participation in HIE. The proposed model can be used by policy makers to find incentive structures that will spur HIE participation in a given community. HIE organizations can also benefit from the proposed model by using it to inform their capacity expansion planning. For instance, HIE organization leaders would be able to prioritize their efforts to seek new customers by identifying those providers at the higher likelihood of joining HIE. Future work will investigate the hospitals' HIE participation decision over time, and extend the application of the model in evaluating other HIE networks and other markets where inter-organizational cooperation for the common good is necessary.

COMPETING INTERESTS

The authors declare no competing interests.

FUNDING

No funding was provided for the completion of this study.

AUTHORS' CONTRIBUTION

DM contributed to the idea conception, study design, model development, and acquisition and analysis of results. FF contributed to the study design, model development and analysis of results. TD and JZ are guarantors and contributed to the study design and analysis of results. All authors contributed equally in preparing and reviewing multiple versions of the manuscript and provided significant intellectual content. All authors read and approved the final version of this manuscript.

Appendix F (continued)

REFERENCES

1 Kohn LT, Corrigan JM, Molla S. *To Err Is Human: Building a Safer Health System*. 2000.

2 Institute of Medicine. *Crossing the Quality Chasm: A New Health System for the 21st Century*. Washington, DC: 2001.

3 Rudin RS, Motala A, Goldzweig CL, *et al.* Usage and Effect of Health Information Exchange. *Ann Intern Med* 2014;**161**:803. doi:10.7326/M14-0877

4 Rahurkar S, Vest JR, Menachemi N. Despite the spread of health information exchange, there is little evidence of its impact on cost, use, and quality of care. *Health Aff (Millwood)* 2015;**34**:477–83. doi:10.1377/hlthaff.2014.0729

5 Adler-Milstein J, Jha AK. Health information exchange among U.S. hospitals: who's in, who's out, and why? *Healthcare* 2014;**2**:26–32. doi:10.1016/j.hjdsi.2013.12.005

6 Furukawa MF, King J, Patel V, *et al.* Despite Substantial Progress In EHR Adoption, Health Information Exchange And Patient Engagement Remain Low In Office Settings. *Health Aff (Millwood)* 2014;:hlthaff.2014.0445 – . doi:10.1377/hlthaff.2014.0445

7 Leu MG, Cheung M, Webster TR, *et al.* Centers speak up: The clinical context for health information technology in the ambulatory care setting. *J Gen Intern Med* 2008;**23**:372–8. doi:10.1007/s11606-007-0488-6

Appendix F (continued)

8 Vest JR, Zhao H, Jasperson J, *et al.* Factors motivating and affecting health information exchange usage. *J Am Med Inform Assoc* 2011;**18**:143–9. doi:10.1136/jamia.2010.004812

9 Finnell JT, Overhage JM. Emergency medical services: the frontier in health information exchange. *AMIA Annu Symp Proc* 2010;**2010**:222–6.http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3041358&tool=pmcentrez&rendertype=abstract

10 Vest JR, Jasperson 'Jon Sean, Zhao H, *et al.* Use of a health information exchange system in the emergency care of children. *BMC Med Inform Decis Mak* 2011;**11**:78. doi:10.1186/1472-6947-11-78

11 Vest JR, Miller TR. The association between health information exchange and measures of patient satisfaction. *Appl Clin Inform* 2011;**2**:447–59. doi:10.4338/ACI-2011-06-RA-0040

12 Office of the National Coordinator for Health Information Technology. Report on Health Information Blocking. https://www.healthit.gov/sites/default/files/reports/info_blocking_040915.pdf

13 Miller AR, Tucker C. Health information exchange, system size and information silos. *J Health Econ* 2014;**33**:28–42.

14 Cohen E. Patients demand: 'Give us our damned data' CNN. 2010.

15 CNN. Patients want records, hospitals turn deaf ear. CNN.com. 2010.

Appendix F (continued)

16 Reps. D. Black and M. Honda. Letter to M. Tavenner and F. Mostashari. 2013.http://op.bna.com/hl.nsf/id/kcpk-99mnkx/$File/711EHRletter.pdf

17 White J. Halth IT Now Coalition. 2015.http://www.healthitnow.org/what-is-information-blocking/

18 Grossman JM, Kushner KL, November EA, *et al.* Creating sustainable local health information exchanges: can barriers to stakeholder participation be overcome? 2008.

19 Adler-Milstein J, DesRoches CM, Jha AK. Health information exchange among US hospitals. *Am J Manag Care* 2011;**17**:761–8.http://www.ncbi.nlm.nih.gov/pubmed/22832592

20 Desai S. Electronic Health Information Exchange, Switching Costs, and Network Effects. *Switch Costs, Netw Eff (November 1, 2014) NET Inst Work Pap* 2014.

21 Ringel JS, Hosken SD, Vollaard BA, *et al.* The Elasticity of Demand for Health Care: A review of the literature and its application to the military health system. Santa Monica, CA: 2002. http://www.rand.org/content/dam/rand/pubs/monograph_reports/2005/MR1355.pdf

22 Sun H, Gao Z, Wu J. A bi-level programming model and solution algorithm for the location of logistics distribution centers. *Appl Math Model* 2008;**32**:610–6. doi:10.1016/j.apm.2007.02.007

23 Feijoo F, Das TK. Design of Pareto optimal cap-and-trade policies for deregulated electricity networks. *Appl Energy* 2014;**119**:371–83. doi:10.1016/j.apenergy.2014.01.019

24 Fampa M, Barroso LA, Candal D, *et al.* Bilevel optimization applied to strategic pricing in competitive electricity markets. *Comput Optim Appl* 2007;**39**:121–42. doi:10.1007/s10589-007-9066-4

25 Hu X, Ralph D. Using EPECs to Model Bilevel Games in Restructured Electricity Markets with Locational Prices. *Oper Res* 2007;**55**:809–27. doi:10.1287/opre.1070.0431

26 Li H, Zhang L, Jiao Y-C. An interactive approach based on a discrete differential evolution algorithm for a class of integer bilevel programming problems. *Int J Syst Sci* 2015;:1–12. doi:10.1080/00207721.2014.993348

27 Saharidis GK, Ierapetritou MG. Resolution method for mixed integer bi-level linear problems based on decomposition technique. *J Glob Optim* 2009;**44**:29–51. doi:10.1007/s10898-008-9291-0

28 Nash JF. Equilibrium points in n-person games. *Proc Natl Acad Sci* 1950;**36**:48–9. doi:10.1073/pnas.36.1.48

29 Pfuntner A, Wier LM, Steiner C. Costs for hospital stays in the united States. *Stat Br* 2010;**146**.

30 Overhage JM, Dexter PR, Perkins SM, *et al.* A randomized, controlled trial of clinical information shared from another institution. *Ann Emerg Med* 2002;**39**:14–23. doi:10.1067/mem.2002.120794

Appendix F (continued)

31 Blumenthal D. Stimulating the Adoption of Health Information Technology. *N Engl J Med* 2009;:1477–9.http://www.nejm.org/doi/full/10.1056/nejmp0901592 (accessed 30 May2013).

32 eHealth Initiative. Health Information Exchange: From Start-up to Sustainability. Washington, DC: 2007. http://www.hci3.org/sites/default/files/files/HRSA CCBH Final Report Revised.pdf

33 GAMS Development Corporation. General Algebraic Modeling System (GAMS). 2013.

34 Chatterjee B. An optimization formulation to compute Nash equilibrium in finite games. In: *Methods and Models in Computer Science, 2009. ICM2CS 2009. Proceeding of International Conference on*. 2009. 1–5.

35 The MathWorks Inc. MATLAB. 2012.

36 Berman O, Zahedi F, Pemble KR. A decision model and support system for the optimal design of health information networks. *IEEE Trans Syst Man Cybern Part C (Applications Rev* 2001;**31**:146–58. doi:10.1109/5326.941839

37 Brennan PF, Ferris M, Robinson S, *et al.* Modeling participation in the NHII: operations research approach. *AMIA Annu Symp Proc AMIA Symp AMIA Symp* 2005;**2005**:76–80.http://www.ncbi.nlm.nih.gov/pubmed/16779005

38 Ferris M, Brennan PF, Tang L, *et al.* Creating operations research models to guide RHIO decision making. *AMIA Annu Symp Proc AMIA Symp AMIA Symp* 2007;**2007**:240–4.http://www.ncbi.nlm.nih.gov/pubmed/18693834

Appendix F (continued)

39 Sridhar S, Brennan PF, Wright SJ, *et al.* Optimizing financial effects of HIE: a multi-party linear programming approach. *J Am Med Inform Assoc* 2012;**19**:1082–8. doi:10.1136/amiajnl-2011-000606

40 Merrill JA, Deegan M, Wilson R V, *et al.* A system dynamics evaluation model: implementation of health information exchange for public health reporting. *J Am Med Inform Assoc* 2013;**20**:e131–8. doi:10.1136/amiajnl-2012-001289

41 Mustafee N, Katsaliaki K, Gunasekaran A, *et al.* Electronic health records: A simulation model to measure the adoption rate from policy interventions. *J Enterp Inf Manag* 2013;**26**:165–82.

42 Yaraghi N, Du AY, Sharman R, *et al.* Network effects in health information exchange growth. *ACM Trans Manag Inf Syst* 2013;**4**:1.

43 Zhu Q, Gunter C, Basar T. Tragedy of anticommons in digital right management of medical records. In: *Proceedings of the 3rd USENIX conference on Health Security and Privacy*. 2012. 10.

44 Strauss AT, Martinez DA, Garcia-Arce A, *et al.* A user needs assessment to inform health information exchange design and implementation. *BMC Med Inform Decis Mak* 2015;**15**:81. doi:10.1186/s12911-015-0207-x

Appendix F (continued)

45 Kruse CS, Regier V, Rheinboldt KT, *et al.* Barriers Over Time to Full Implementation of Health Information Exchange in the United States. *JMIR Med Inf* 2014;**2**:e26. doi:10.2196/medinform.3625

46 Sheikh A, Sood HS, Bates DW. Leveraging Health Information Technology to Achieve the 'Triple Aim' of Healthcare Reform. *J Am Med Inform Assoc* 2015;**44**:1–9. doi:10.1093/jamia/ocv022

47 O'Malley AS, Bond AM, Berenson RA. Rising hospital employment of physicians: better quality, higher costs? *Issue Br Cent Stud Heal Syst Chang* 2011;:1–4.http://www.ncbi.nlm.nih.gov/pubmed/21853632

48 O'Malley AS. Testimony to the interoperability task force of the health IT policy committee, ONC. 2015.