Final Report

Development of a community-wide real-time health information exchange–based hospital readmission risk prediction and notification system for office-based practices: A feasibility and evaluation study

Principal Investigator

Hadi Kharrazi, [a b] *MHI, MD, PhD*

Team Members

Jonathan Weiner, [a] *DrPH*

Martha Sylvia, [b c] *PhD*

Daniel Brotman, [b] *MD*

Klaus Lemke, [a] *PhD*

Tom Richards, [a] *MS*

Elyse Lasser, [a] *MS*

Fardad Gharghabi, [a] *MS, MD*

Brett Cropp, [b] *MS*

Organizations

[a] Johns Hopkins Bloomberg School of Public Health

[b] Johns Hopkins School of Medicine

[c] Medical University of South Carolina

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Federal Project Officer

Ellen Makar (Ellen.Makar@ahrq.hhs.gov)

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❖ Abstract

Purpose: To derive and validate a 30-day hospital readmission risk prediction model (RRPM) based on Admission Discharge, and Transmission (ADT) messages transacted by Health Information Exchange (HIE) entities.

Scope: Preventing avoidable hospital readmissions is considered a key opportunity for reducing waste in healthcare. An HIE can significantly contribute to preventable hospital readmissions within a community. Currently, RRPMs are very common, using post-facto health plan claims and hospital administrative databases, but they have rarely utilized HIE data for derivation or validation. Using HIE data for readmission prediction enables the models to execute in real time and predict interhospital readmissions in addition to intrahospital readmissions.

Methods: Significant readmission variables were identified through a systematic review. The readmission variables were then mapped with the ADT message segments. The Johns Hopkins ACG® System was used to stratify the data and develop the RRPM library of predictive models for readmission. Model performance was compared with existing readmission prediction models. Issues with ADT data quality variability among hospitals were detected, and the research team is planning to identify effective approaches to develop RRPMs based on common ADT data segments.

Results: The research team developed a library of RRPMs that show an acceptable predictive power (AUC ranging between .59 and .63) to detect potential preventable readmissions.

Conclusion: Readmission prediction models can be developed based on transactional HIE data; however, more work is needed to ensure higher accuracy and increased generalizability for the models.

Key Words: 30-day hospital readmission; predictive modeling; health informatics exchange

❖ Purpose

Current readmission risk predictive models (RRPMs) are developed based on post-facto health plan claims and hospital administrative databases; however, RRPMs are rarely derived or validated using real-time HIE (Health Information Exchange) data. The aim of this research study is to develop and evaluate HIE-based real-time RRPM scores for patients discharged from Maryland hospitals. This research also plans to assess and improve the RRPM's predictive accuracy via an iterative process that will integrate and evaluate non-HIE data sources in order to explore data that will be available to the HIEs in the near future.

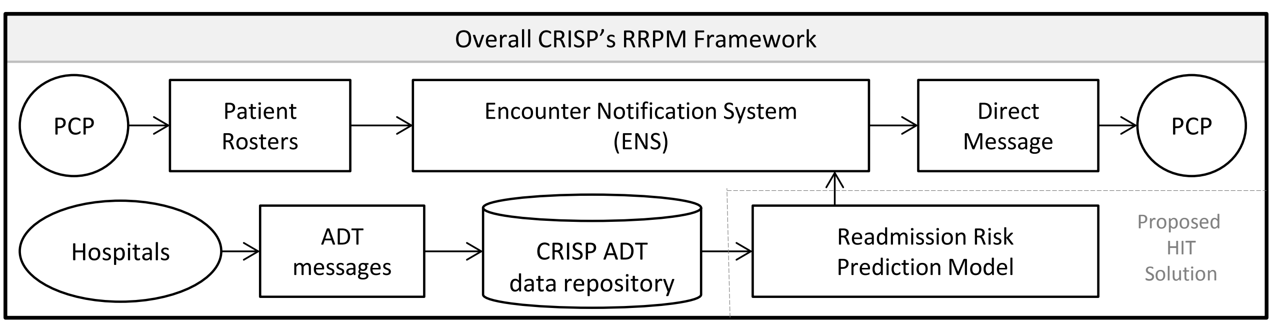

Figure 1: Integration of the proposed health IT solution in Maryland's HIE
PCP: Primary Care Physician; CRISP: Chesapeake Regional Information System for our Patients;
ADT: Admission Discharge and Transmission

As depicted in Figure 1, the overall purpose of this project is to develop the RRPM based on data available in Admission Discharge, and Transmission (ADT) messages that are transmitted by the Chesapeake Regional Information System for our Patients (CRISP), which is the designated Maryland statewide HIE. When new ADT messages are received by CRISP, the RRPM calculates readmission scores and assigns them to patients. Then, a note is sent out to primary care physicians

(PCPs) who have enrolled those patients at CRISP. PCPs will receive the notification via CRISP's Encounter Notification System (ENS), which uses the direct messaging standard.

❖ Scope

Background

Hospitals account for nearly $1 trillion (~30%) of US healthcare spending [1]. Preventing avoidable hospital readmissions is considered a key opportunity for reducing waste in healthcare [2]. Around 18% of inpatients are readmitted to hospitals within 30 days [3]. It is estimated that almost 14% of Medicare readmissions – costing $12 billion annually [4] – are preventable [5]. Despite hospital-centric interventions, [5] 'avoidable' readmissions have increased steadily over the past decade [6]. Hospital readmission metrics have been criticized [7] for their lack of specificity in differentiating inpatient- and outpatient-caused readmissions [8] and their ambiguity in leveraging ambulatory resources to detect and manage high-risk patients [9].

Ambulatory care is integral to reducing hospital readmissions [10,11]. Patients lacking timely primary care physician (PCP) follow up are 10 times more likely to be readmitted [12]. Around 75% of paper-based discharge summaries are not received by PCPs [13], and 50% of readmitted Medicare patients did not have a follow-up office visit [14]. These transition failures are exacerbated by various disconnects between in- and outpatient settings, such as fewer PCPs who provide inpatient care; PCPs who may be distant from the hospitals; and uncommon interoperability of PCP-hospital electronic health records (EHRs) [15]. A cross-provider health IT system can assist the PCP in reducing avoidable readmissions [15]. Such a system can provide PCPs with actionable real-time notification of a patient's risk for readmission during phases of the hospital-to-office care transition.

A Health Information Exchange (HIE) can significantly contribute to preventable hospital readmissions within a community [15,16,17]. Through information sharing, HIEs can improve coordination between hospitals and PCPs [17,18], improving the promptness and effectiveness of follow-up care. Evidence suggests that this can be accomplished by increased discharge data timeliness, data completeness, point-of-care notification, and cross-provider aggregated patient histories [13,17,19,20,21].

Context

As of 2012, Maryland's HIE ('CRISP') has collected real-time data on ~4 million patients, including 250k patients registered by 400+ PCPs as part of a monitoring system known as the Encounter Notification System (ENS) [22]. ENS notifies PCPs of sentinel events, including admission and readmission. CRISP also shares monthly readmission reports [16]. The reporting system is a considerable advance, but it lacks an actionable tool to identify the patient's probability of readmission or real-time decision support information to assist the PCP. The development and testing of HIE-based real-time readmission risk information for PCPs is the focus of this project.

Interest and saliency in the activities of this project will be catalyzed by the Maryland hospital and PCP communities' advanced stage of readiness to avoid readmissions. Most hospitals in Maryland are not paid for any public, private, or self-pay readmissions due the Maryland's all-payer rate setting commission [23]. In Maryland hospitals, discharge support teams have received special training, and almost all Maryland PCPs are now part of one of the most advanced patient-centered–care medical home (PCMH) initiatives in the nation [24].

The project's technical development is based on the Johns Hopkins ACGs (adjusted clinical groups, formerly ambulatory care groups) that focus on developing and testing predictive models. ACGs are one of the most advanced and widely used digital data-based predictive modeling tool in common use [25]. ACG has been used for two decades across the nation and in 15 other countries and has been applied to 60+ million patients to help predict various healthcare events (including hospitalization) using claims and admin data [26].

Currently, readmission risk predictive models (RRPMs) are very common using post-facto health plan claims and hospital administrative databases [27], but they have rarely utilized HIE data for derivation or validation [15]. The aim of this study is to develop and evaluate such HIE-based real-time RRPM-derived scores for all patients discharged from Maryland hospitals. This project also will assess and improve the RRPM's predictive accuracy via an iterative process that will integrate and evaluate non-HIE data sources in order to explore data soon to be available to the HIE.

Settings

The study was conducted at the Johns Hopkins School of Public Health in Baltimore, Maryland, in collaboration with the Chesapeake Regional Information System for our Patients (CRISP) in Columbia, Maryland.

The Johns Hopkins School of Public Health (JHSPH) is a higher education institute offering graduate education of research scientists and public health professionals. JHSPH's fields of interest are diverse, including the primary intellectual disciplines of public health; quantitative sciences, such as biostatistics, epidemiology, and demography; basic and applied research; social policy; planning, management, and evaluation of the delivery of health services; and the biological and environmental health sciences. JHSPH has nearly 2,000 students in masters and doctoral programs and over 485 full-time faculty members.

The Chesapeake Regional Information System for our Patients (CRISP) is designated as the Maryland statewide Health Information Exchange (HIE) by the Maryland Health Care Commission. CRISP is a not-for-profit membership corporation advised by a wide range of stakeholders responsible for the healthcare of Maryland's citizens. They receive input and advice from patients; hospital systems; physicians; insurance providers; technology providers; privacy advocates; public health officials; and advocates for seniors, the uninsured, and the medically underserved. CRISP has a large development facility and a HIPAA-compliant data center for HIE activity.

Participants

NA

Incidence

NA

Prevalence

NA

❖ Methods

Study Design

Developing the HIE-derived RRPM included the following phases: (1) mapping ADT message segments with significant readmission variables; (2) training/deriving an optimized RRPM library based on CRISP's ADT data repository; and (3) comparing the accuracy of models derived from 'required' versus 'optional' ADT data elements.

Evaluating the HIE-based RRPM included the following steps: (1) comparing the model's performance against the common predictive models; and (2) validating the accuracy of RRPMs by a retrospective split-validation method (i.e., 2/3 to 1/3 split).

Data Sources/Collection

As of 2012, Maryland's HIE (known as 'Chesapeake Regional Information System for our Patients' – CRISP) collects data from 48 state hospitals (100% demographics, 52% lab results, 67% radiology reports, and 64% clinical reports), six long-term care facilities, eight radiology centers, and two national labs [28]. Similar to other HIEs, HL7 ADT messages [29] (admission, discharge, and transfer) are the most common data type received by CRISP. CRISP's Encounter Notification System (ENS) [22] enables the notification of participating providers of sentinel events, such as readmissions. CRISP generates and shares a monthly readmission report [16] with care coordinators, which includes intra- and interprovider readmission data (see Figure 2 for a complete picture of data processing pipelines at CRISP).

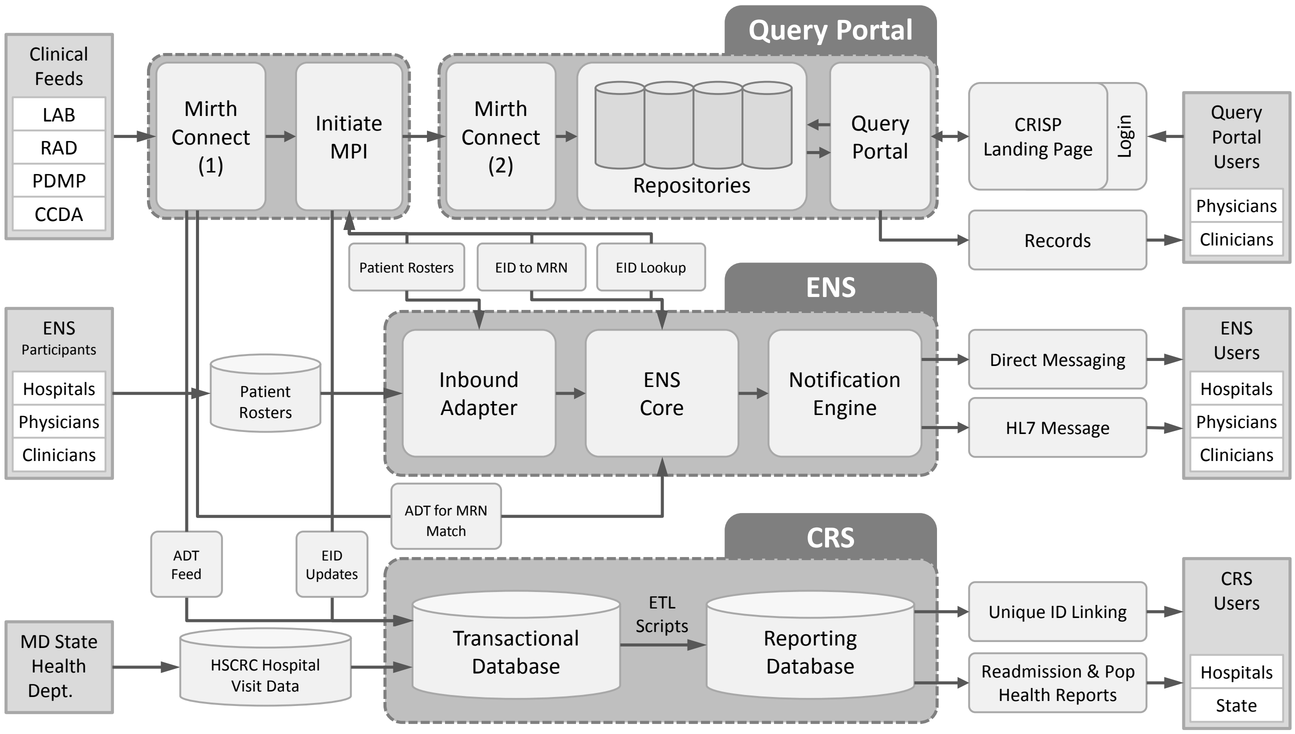

Figure 2: CRISP's information architecture and data collection. ADT: Admission Discharge and Transfer; CCDA: Consolidated Clinical Document Architecture; CRS: CRISP Reporting System; EID: Enterprise Identifier; ENS: Encounter Notification System; ETL: Extract Transform and Load; HL7: Health Level 7; HSCRC: [Maryland] Health Services Cost Review Commission; MPI: Master Patient Index; MRN: Medical Record Number; PDMP: Prescription Drug Monitoring Program; Pop: Population; RAD: Radiology.

Interventions

NA

Measures

NA

Limitations

Limitations included the following: (a) Although the CRISP ADT data repository has an acceptable range of segment completeness, the number of potential readmission predictors was limited. Thus, this research did not hypothesize that CRISP-derived RRPMs will obtain a significantly higher accuracy compared with claims or EHR-derived RRPMs. Instead, the aim was to explore an HIE-derived RRPM library with sufficient discriminatory power that can leverage the real-time interprovider nature of CRISP – along with the high potential of generalizability to other HIEs – to achieve a broad effect size across the community of CRISP stakeholders. (b) The model does not discriminate against age groups and will include the pediatric population in the derivation process [30,31]. Plans are made to explore data partitioning options. (c) The external validity of CRISP-derived RRPMs will be limited to HIEs with similar depth and type of data collection to CRISP. A separate research study should be conducted to evaluate the generalizability of CRISP-derived RRPM in a larger pool of HIEs. (d) Data privacy and access issues were limiting factors in the ability to access the full spectrum of HIE data.

❖ Results

Principal Findings

Common HIE data streams/structures are a viable source of information to develop and evaluate RRPMs; however, pilot findings indicate that the variability of data patterns received from different HIE stakeholders (i.e., various hospitals) may limit the generalizability of fixed predictive models. The study team has envisioned a dynamic approach to generate a library of RRPMs accustomed to various stakeholders of HIEs. The research team developed a library of RRPMs that show an acceptable predictive power (AUC ranging between .59 and .63) to detect potential preventable readmissions. The study is currently in its final phase, and remaining validation results (including accuracy of the proposed RRPM) will be published in a peer-reviewed journal.

Outcomes

NA

Significance and Implications

Scientific impact: The proposed project developed and evaluated RRPMs (readmission risk predictive models) based on 'readmission-related risk factors' extracted from ADT messages that are exchanged and collected by CRISP. To overcome the challenge of limited predictors in the current ADT data, the research team has leveraged a set of statistical techniques and informatics solutions. For example, due to the heterogeneity of data sources in an HIE, a series of RRPMs was derived and stored in a model library that will be triggered for the closest matching patient profile based on various matching solutions (e.g., decision tree on segment matching [32]). These informatics advancements can produce significant impact on the application of predictive modeling in other settings, specifically when the completeness of data elements (predictors, ADT segments) is variable.

Besides future hospitalizations, the current ACG predictive models have multiple prediction capabilities, such as future costs estimations and unexpectedly high pharmacy use predictions [25]. ACGs are mainly designed and deployed on claims data for prediction modeling (though outside the US they are derived mainly with EHR data). The application of ACGs in an HIE environment will substantially empower the ACG's research team to explore the application of other ACG predictive models in HIE settings, such as predicting patients at high-risk for increased resource usage among HIE stakeholders and identifying patients who would benefit the most from an intensive cross-provider disease management outreach.

Practical impact: Our HIE-derived RRPM is intended to have a positive impact on CRISP's (and all other HIEs') push toward value-added services to their stakeholders. Currently, CRISP delivers monthly reports on readmission to hospital care coordinators [16] and notifies individual cases of admission or readmission to registered PCPs [22]. The HIE-derived RRPM can boost CRISP's efforts to provide new actionable services to its stakeholders. Within a reasonable timeframe and for a nominal fee, CRISP can further integrate and evaluate the RRPM into its day-to-day operations. The impact of an operational RRPM for CRISP could include (a) enhancing the health quality outcome of ~4 million Marylanders by reducing avoidable readmissions; (b) motivating PCPs to join the CRISP network and eventually share EHR data; (c) leveraging the economical savings of reduced readmissions as a future funding source; and (d) implementing fee-for-service access for providers to use an advanced version of RRPM (i.e., integrated with an extra decision support system). The latter will empower CRISP's sustainability – a concern of most HIEs[33,34] – in long term.

Larger-scale impact: As of 2011, more than 200 HIEs have launched [18,35], touching almost every state. Active HIEs exchange the information of more than 100 million patients [18]. Because of this broad population coverage, HIEs can play a key role in reducing preventable hospital readmissions [15,17,36]. This feasibility project can notably influence the HIEs' roles in reducing readmissions by (a) increasing the generalizability of the model to other HIEs; (b) improving the customizability of the model for each provider; and (c) enhancing the practicality of the model through the interconnected HIE continuum. In fact, predictive models that are developed based on an HIE data repository are more likely to be successfully utilized in other HIEs because of the stringent and similar standards [29] used in transmitting messages from providers to HIEs and also in connecting HIEs together [37].

Policy impact: Forecasting-based interventions might have uncertain effectiveness and focus on cost savings rather than long-term health. Policymakers should adopt strategies that address these concerns in order to maximize the benefit of healthcare forecasting on the long-term health of patients [38]. Thus, the policy outcomes of this research can be concentrated on two noneconomic perspectives: (a) Interprovider readmissions: cross-provider readmission is not well defined under the ACA [39]. CMS does not clarify the policies of reimbursement adjustment for interprovider-caused readmissions (e.g., patient readmitted to another hospital within 30 days of discharge). The results of this study can be used to shed light on the effect of interprovider readmissions when calculating readmission risk scores. (b) Future data integration: HIEs are constantly incorporating, or planning to incorporate, new health data sources [34]. This project has generated a report on the value of expanded ADT data sources. The results can help HIEs in making a decision on what type of ADT segments to collect in the near future.

Discussion

This research project is novel in using HIE infrastructure on three perspectives: use of new data types to train and test an RRPM; use of the HIE as a hub to deliver RRPM support; and the potential to replicate RRPMs in other HIEs beyond CRISP.

New types of data: The new types and sources of HIE data are simultaneously a challenge and an advantage for constructing readmission predictive models. The challenge is the relatively shallow depth of the current messages collected by HIEs that contain admission, discharge, and transfer information data (i.e., ADT messages). ADT messages have multiple segments with varying completeness due to provider variability and the optional status of some data segments. In this early stage of HIE data capture, creating the best model may require an innovative approach that utilizes a hybrid of statistical models (e.g., hierarchical logistic regression [32]). The advantage of HIE data lies in its unique features that are not common in traditional source of data for readmission prediction models, including timeliness of data, large population sets, and interprovider capabilities. These features make HIEs an interesting alternative to claims and EHRs to explore the development of innovative readmission predictive models.

HIE-RRPM hub: Utilizing the HIE as the center hub for RRPM calculation and notification (rather than a single health insurer or provider) is an innovative approach to delivering a decision support risk score across the continuum of healthcare. RRPM feedback can be provided in real time to a range of stakeholders from inpatient care, to ambulatory care, to home care. The growing functionalities of HIEs and the possibilities to integrate RRPM notification in new workflow elements of this continuum enable HIEs to act proactively in reducing avoidable readmissions.

RRPM generalizability: If an acceptable accuracy is achieved, the RRPM can provide a large effect size due its generalizability to other HIE settings. Most HIEs adhere to the same standards and collect conventional ADT message types, thus making the minimalistic RRPM highly replicable. In addition, as HIEs grow vertically (i.e., data points collected per event per patient) and new commonly agreed upon levels of data depth are established in the community, the model can be upgraded to incorporate the new data depth and possibly increase its accuracy.

Conclusions

HIEs are a critical source of data for predicting 30-day interprovider hospital readmission. Generalizability of HIE-based RRPMs is a concern and needs additional investigation.

❖ Future Work

Near future: (1) Increase external validity: Investigate the model's derivation process and validation results in other HIE settings. (2) Increase internal validity: Request reporting of optional ADT segments with low coverage and add in model training, and integrate massive soft data, such as public health resource utilization through GIS triangulation. (3) Quantitative measures of effectiveness: Conduct a moderate-scale prospective, controlled study to measure the effect of the readmission prediction notification system in reducing 30-day hospital readmission in the treatment group (with access to the model) compared with the control group (with no access to the model).

Distant future: (1) Increase external validity: Conform the predictive model to the Nationwide Health Information Network (NwHIN) infrastructure that is a collection of interconnected HIEs [40,41]. (2) Increase internal validity: Train and validate the predictive model on an aggregated database of patients that includes an aggregated merger of their HIE data (e.g., CRISP), claims, and EHR data; training will incrementally add various data sources to measure their effect size in increasing the model's accuracy.

❖ List of Publications and Products

Swain MJ, Kharrazi H. Feasibility of 30-day hospital-readmission prediction modeling based on health information exchange data. International Journal of Medical Informatics (IJMI) 2015; 84(12):1048-56. PMID: 26412010

❖ Glossary of Acronyms

ACA	Affordable Care Act *(see PPACA)*
ACG	Adjusted Clinical Groups
ADT	Admit Discharge Transfer
AHRQ	Agency for Healthcare Research and Quality
CMS	Centers for Medicare & Medicaid Services
CPHIT	Center for Population Health Information Technology
CRISP	Chesapeake Regional Information System for our Patients (the Maryland HIE)
DHMH	[Maryland] Department of Health and Mental Hygiene
EHR	Electronic Health Record
ENS	Encounter Notification System
GIS	Geographic Information Systems
HIE	Health Information Exchange
HIPAA	Health Insurance Portability and Accountability Act
HL7	Health Level 7 [Messaging Standard]
HSCRC	[MD] Health Services Cost Review Commission
IJMI	International Journal of Medical Informatics
JHU	Johns Hopkins University
MD	Maryland
MPI	Master Patient Index
NCQA	National Committee for Quality Assurance
NHIN	National Health Information Network
NwHIN	Nationwide Health Information Network
ONC	Office of the National Coordinator [for Health Information Technology]
PACR	Plan All-Cause Readmissions
PCMH	Patient-Centered Medical Home
PCP	Primary Care Physician
PPACA	Patient Protection and Affordable Care Act
RRPM	Readmission Risk Predictive Model

❖ References

1. Centers for Medicare and Medicaid Services (CMS). National Health Expenditure Fact Sheet. *Centers for Medicare & Medicaid Services*. 2011. Available at: http://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/NHE-Fact-Sheet.html. Accessed Jan 7, 2013.

2. National Committee for Quality Assurance. Insights for improvement - Reducing readmissions: Measuring health plan performance. 2012. http://www.ncqa.org/Portals/0/Publications/2012%20BI_NCQA%20ReAdMi%20_Pub.pdf. Accessed Jan 2, 2013.

3. Centers for Medicare and Medicaid Services (CMS). Medicare hospital compare quality of care. http://www.hospitalcompare.hhs.gov. Accessed Jan 5, 2013.

4. Department of Health and Human Services. Hospital inpatient prospective payment systems for acute care hospitals and the long-term care hospital prospective payment system and fiscal year 2013 rates. *Federal Register*. http://www.gpo.gov/fdsys/pkg/FR-2012-08-31/pdf/2012-19079.pdf. Accessed Jan 4, 2013.

5. Centers for Medicare and Medicaid Services (CMS). Report to Congress: Promoting greater efficiency in Medicare. Payment policy for inpatient readmissions. 2007. http://www.medpac.gov/chapters/Jun07_Ch05.pdf. Accessed Jun 2, 2012.

6. Harvath BS. Hospital readmission issues: Past & present. 2011. http://www.ehcca.com/presentations/readsummit3/harvath_pc.pdf. Accessed Jan 4, 2013.

7. van Walraven C, Jennings A, Taljaard M, et al. Incidence of potentially avoidable urgent readmissions and their relations to all-cause urgent readmissions. *Canadian Medical Association Journal*. 2011;183(14):E1067-E1072.

8. Joynt KE, Jha AK. Thirty-day readmissions: truth and consequences. *N Engl J Med*;366(15):1366-1369.

9. Amarasingham R, Moore BJ, Tabak YP, et al. An automated model to identify health failure patients at risk for 30-day readmission or death using electronic medical record data. *Medical Care*. 2010;48(11):981-988.

10. Brock J, Mitchell J, Irby K, et al. Association between quality improvement for care transitions in communities and rehospitalizations among medicare beneficiaries. *JAMA*. 2013;309(4):381-391.

11. van Walraven C, Seth R, Austin PC, Laupacis A. Effect of discharge summary availability during post-discharge visits on hospital readmission. *JGIM*. 2002;17(3):186-192.

12. Misky G, L WH, Coleman EA. Post-hospitalization transitions: Examining the effects of timing of primary care provider follow-up. *Journal of Hospital Medicine*. 2010;5(7):392-397.

13. Kripalani S, T JA, Schnipper JL, Coleman EA. Promoting effective transitions of care at hospital discharge: a review of key issues for hospitalists. *Journal of Hospital Medicine*. 2007;2(5):314-323.

14. Jencks SF, Williams MV, Coleman EA. Rehospitalizations among patients in the Medicare fee-for-service program. *N Engl J Med*. 2009;360:1418–1428.

15. Healthcare Information and Management Systems Society (HiMSS) - The hospital readmission workgroup. Reducing readmissions: Top ways information technology can help. 2012. http://www.himss.org/content/files/ControlReadmissionsTechnology.pdf. Accessed Jan 6, 2013.

16. The Chesapeake Regional Information System for our Patients. CRISP Encounter Reporting System. 2012. http://www.crisphealth.org/LinkClick.aspx?fileticket=dQdEOAKc1Fo%3D&tabid=172&mid=780. Accessed Jan 9, 2013.

17. Jones SS, Frieberg MW, Schneider EC. Health information exchange, health information technology use, and hospital readmission rates. Paper presented at: AMIA Symposium, 2011:644-653; Washington, DC.

18. eHealth Initiative. The state of health information exchange in 2010: Connecting the nation to achieve meaningful use. 2010. http://www.ehealthinitiative.org/images/stories/hie_toolkit/documents/Final_Report.pdf. Accessed Jan 15, 2013.

19. Boutwell AE, Johnson MB, Rutherford P, et al. An early look at a four-stat initiative to reduce avoidable hospital readmissions. *Health Affairs*. 2011;30(7):1272-1280.

20. McKethan A, Brammer C, Fatemi P, et al. An early status report on the beacon communities' plans for transformation via health information technology. *Health Affairs*. 2011;30(4):782-788.

21. Pilkington W. Use of health information to improve care: The southern Piedmont beacon community grant. *NC Med J*. 2011;72(3):234-236.

22. The Chesapeake Regional Information System for our Patients. CRISP Encounter Notification System. Keeping you connected to your patients. 2012. http://www.crisphealth.org/LinkClick.aspx?fileticket=PPKbVlpNstQ%3D&tabid=272. Accessed Dec 12, 2012.

23. Maryland Health Services Cost Review Commission (HSCRC). Template for review and negotiation of an admission-readmission revenue hospital payment constraint program. 2011. http://www.hscrc.state.md.us/documents/HSCRC_PolicyDocumentsReports/ApprovedPolicyPapersStaffRecommendations/2011/ARR_Template_RecommendationFinal_adopted_01-12-11.pdf. Accessed Jan 5, 2013.

24. Maryland Department of Health and Mental Hygiene (DHMH). Maryland Multi-Payer Patient-Centered Medical Home Program (MMPP). 2012. http://mhcc.maryland.gov/pcmh/documents/PCMH%20program%20%20description_073112.pdf. Accessed Jan 22, 2013.

25. The Johns Hopkins ACG System. ACG Predictive Models (ACG-PM). http://www.acg.jhsph.org/index.php?option=com_content&view=article&id=59&Itemid=150. Accessed Jan 9, 2013.

26. The Johns Hopkins ACG System. ACG Coordination Markers: Care Management Support. http://www.acg.jhsph.org/index.php?option=com_content&view=article&id=128&Itemid=166. Accessed Jan 9, 2013.

27. Kansagara D, Englander H, Salanitro A, et al. Risk prediction models for hospital readmission: A systematic review. *JAMA*. 2011;306(15):1688-1698.

28. The Chesapeake Regional Information System for our Patients. Participating providers. 2013. http://www.crisphealth.org/ForPatients/ParticipatingProviders/tabid/241/Default.aspx. Accessed Jan 12, 2013.

29. Health Level 7. HL7 version 3 standard: Patient administration (admits, discharges, and transfers). 2012. http://www.hl7.org/implement/standards/product_brief.cfm?product_id=92. Accessed Jan 8, 2013.

30. Berry JG, Toomey SL, Zaslavsky AM, et al. Pediatric readmission prevalence and variability across hospitals. *JAMA*. 2013;309(4):372-380.

31. Srivastava R, Keren R. Pediatric readmissions as a hospital quality measure. *JAMA*. 2013;309(4):396-398.

32. Austin PC. A comparison of regression trees, logistic regression, generalized additive models, and multivariate adaptive regression splines for predicting AMI mortality. *Statistics in Medicine*. 2006;26:2937-2957.

33. eHealth Initiative. Preliminary key findings: 2012 survey on Health Information Exchange. 2012. http://www.ehealthinitiative.org/resources/finish/54-annual-surveys/578-preliminary-key-findings-2012-survey-on-health-information-exchange.html. Accessed Jan 4, 2012.

34. eHealth Initiative. 2011 report on Health Information Exchange: Sustainable HIE in changing landscape. 2011. http://www.cfrhio.org/images/2_2011_Report_on_Health_Information_Exchange_-_Sustainability_Report.pdf. Accessed Jan 5, 2013.

35. American Hospital Association (AHA). Health information exchange projects what hospitals and health systems need to know. 2006. http://www.aha.org/content/00-10/AHARHIOfinal.pdf. Accessed Jan 10, 2013.

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? *JAMIA*. 2011;18:853-858.

37. Connect Community Portal. Role in the nationwide health information network. http://www.connectopensource.org/about/role-in-the-nhin. Accessed Jan 22, 2013.

38. Wharam JF, Weiner JP. The promise and peril of healthcare forecasting. *The American Journal of Managed Care*. 2012;18(3):e82-e85.

39. United States Senate. HR3590: The Patient Protection and Affordable Care Act. 2009. http://www.gpo.gov/fdsys/pkg/BILLS-111hr3590enr/pdf/BILLS-111hr3590enr.pdf. Accessed Jan 12, 2013.

40. Department of Health and Human Services (DHHS). What is the NHIN? http://www.healthit.gov/sites/default/files/what-Is-the-nhin--2.pdf. Accessed Jan 15, 2013.

41. Office of National Coordinator for Health Information Technology (ONC-HIT). Nationwide Health Information Network (NwHIN). 2012. http://www.healthit.gov/policy-researchers-implementers/nationwide-health-information-network-nwhin. Accessed Jan 5, 2013.