

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

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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 health care. 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 inter-hospital readmissions in addition to intra-hospital 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.

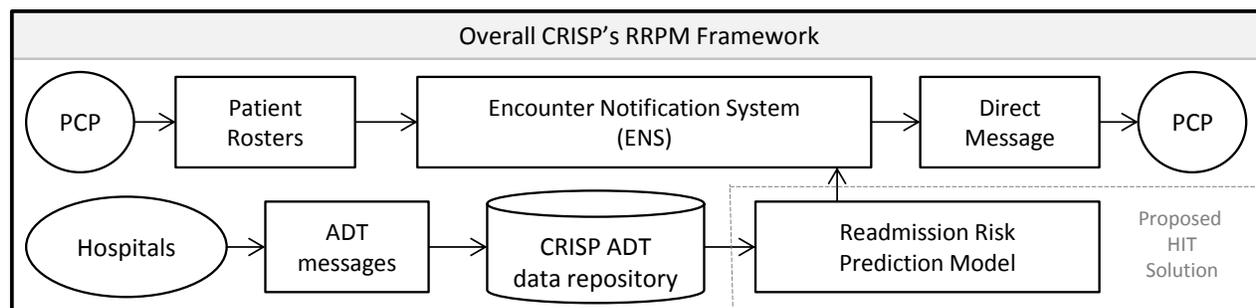


Figure 1: Integration of the proposed health IT solution in the Maryland's HIE
PCP: Primary Care Physician; CRISP: Chesapeake Regional Information System for Our Patients;
ADT: Admission Discharge and Transmission

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 health care spending¹. Preventing avoidable hospital readmissions is considered a key opportunity for reducing waste in health care². Around 18% of inpatients are readmitted to hospitals within 30 days³. It is estimated that almost 14% of Medicare readmissions – costing \$12 billion annually⁴ – are preventable⁵. Despite hospital-centric interventions, ⁵ 'avoidable' readmissions have increased steadily over the last decade⁶. Hospital readmission metrics have been criticized⁷ for their lack of specificity in differentiating inpatient- and outpatient-caused readmissions⁸ and ambiguity in leveraging ambulatory resources to detect and manage high-risk patients⁹.

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 readmitted¹². Around 75% of paper based discharge summaries are not received by PCPs¹³ and 50% of readmitted Medicare patients did not have a follow up office visit¹⁴. These transition failures are exacerbated by various disconnects between in and outpatient settings such as: fewer PCPs provide inpatient care; PCPs may be distant from the hospitals; and, interoperability of PCP-hospital electronic health records (EHRs) are uncommon¹⁵. A cross provider health IT system can assist the PCP in reducing avoidable readmissions¹⁵. Such a system can provide PCPs with actionable real-time notification of 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 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 reports¹⁶. 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 commission²³. In Maryland hospitals, discharge support teams have received especial training and almost all Maryland PCPs are now part of one of the most advanced patient centered care medical home (PCMH) initiatives in the nation²⁴.

The project's technical development is based on The Johns Hopkins ACGs (adjusted clinical groups, formerly ambulatory care groups) that focuses on developing and testing predictive models. ACGs are one of the most advanced and widely used digital data based predictive modeling tool in common use²⁵. ACG has been used for two decades across the nation and in 15 other countries, and applied to 60+ million patients to help predict various healthcare events (including hospitalization) using claims and admin data²⁶.

Currently readmission risk predictive models (RRPMs) are very common using post-facto health plan claims and hospital administrative databases²⁷, but they have rarely utilized HIE data for derivation or validation¹⁵. 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 assesses and improves 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 Johns Hopkins School of Public Health in Baltimore, Maryland in collaboration with the Chesapeake Regional Information System for Our Patients (CRISP) in Columbia, Maryland.

Johns Hopkins School of Public Health (JHSPH) is a higher education institute with 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.

Chesapeake Regional Information System for Our Patients (CRISP) is the designated 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), 6 long-term care facilities, 8 radiology centers, and 2 national labs²⁸. Similar to other HIEs, HL7 ADT-messages²⁹ (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-report¹⁶ with care coordinators, which includes intra- and inter-provider readmission data (see figure 2 for a complete picture of data processing pipelines at CRISP).

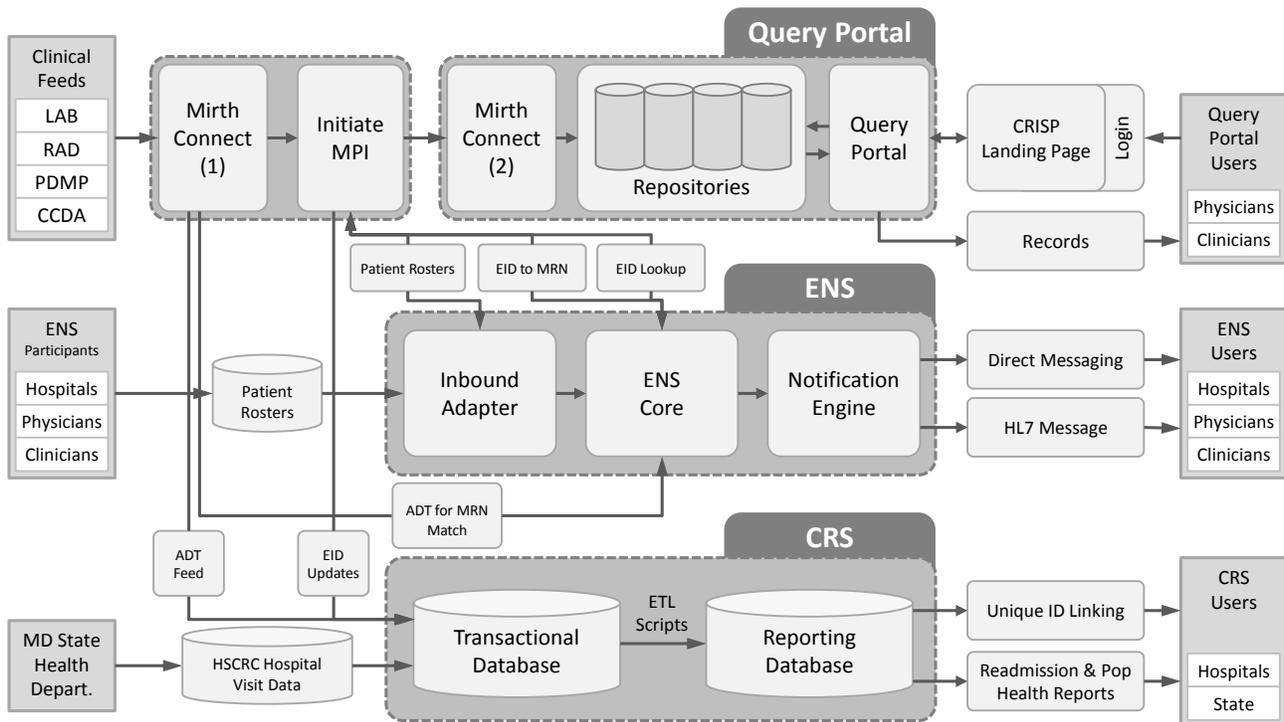


Figure 2: CRISP's information architecture and data collection. ADT: Admission Discharge and Transfer; CCDA: Consolidated Clinical Document Architecture; CRS: CRISP Reporting System; EID: Enterprise Identifier; ENS: Encounter Notification System; ETL: Extract Transform and Load; HL7: Health Level 7; 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: (a) Although 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 to claims- or EHR-derived RRPMS. Instead, the aim was to explore an HIE-derived RRPMS library with sufficient discriminatory power that can leverage the real-time inter-provider nature of CRISP – along with the high potential of generalizability to other HIEs – to achieve a broad effect size across the community of CRISP stakeholder. (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 RRPMS in a larger pool of HIEs. (d) Data privacy and access issues were limiting factors 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 were derived and stored in a model library that will be triggered for the closest matching patient profile based on various matching solution (e.g., decision tree on segment matching³²). 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 unexpected high pharmacy use predictions²⁵. 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's predictive models in HIE settings such as: predicting 'high-risk for increased resource usage' patients 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 towards value-added services to their stakeholders. Currently CRISP delivers monthly reports on readmission to hospital care coordinators¹⁶, and notifies individual cases of admission or readmission to registered PCPs²². The HIE-derived RRPM can boost CRISP's efforts to provide new actionable services to its stakeholders. Within a reasonable timeframe and 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 a 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 patients¹⁸. Due to 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' role 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 due to stringent and similar standards²⁹ used in transmitting messages from providers to HIEs and also in connecting HIEs together³⁷.

Policy Impact: Forecasting-based interventions might have uncertain effectiveness and focus on cost savings rather than long-term health. Policy makers should adopt strategies that address these concerns in order to maximize the benefit of healthcare forecasting on the long-term health of patients³⁸. Thus, the policy outcomes of this research can be concentrated on two non-economic perspectives: (a) Inter-provider readmissions: cross-provider readmission is not well defined under the ACA³⁹. CMS does not clarify the policies of reimbursement adjustment for inter-provider-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 inter-provider readmissions when calculating readmission risk scores. (b) Future data integration: HIEs are constantly incorporating, or planning to incorporate, new health data sources³⁴. 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; employ HIE as a hub to deliver RRPM support; and, potential to replicate RRPM 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 optional status of some data segments. In this early stage of the HIE data capture, creating the best model may require an innovative approach that utilizes a hybrid of statistical models (e.g., hierarchical logistic regression³²). The advantage of HIE data relies 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 inter-provider 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 possibilities to integrate RRPM notification in new workflow elements of this continuum, enables 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 levels of data depth is 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 inter-provider hospital readmission. Generalizability of HIE-based RRPMs is a concern and needs further 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: requesting optional ADT-segments with low coverage to be reported and added in model training, and integrating 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 to the control group (with no access to the model).

Distant future: (1) Increase external validity: conforming the predictive model to Nationwide Health Information Network (NwHIN) infrastructure that is a collection of inter-connected 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 (<i>see PPACA</i>)
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

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