International Journal of Medical Informatics 84 (2015) 1048–1056

Contents lists available at ScienceDirect

International Journal of Medical Informatics

journal homepage: www.ijmijournal.com

Feasibility of 30-day hospital readmission prediction modeling based on health information exchange data

Matthew J. Swain [a,*], Hadi Kharrazi [b]

[a] U.S. Department of Health and Human Services, United States
[b] Johns Hopkins Bloomberg School of Public Health, Center for Population Health Information Technology, Baltimore, United States

ARTICLE INFO

Article history:
Received 28 April 2015
Received in revised form 6 August 2015
Accepted 11 September 2015

Keywords:
Health information exchange
Hospital readmissions
Health information organization
Risk prediction model
Health information technology

ABSTRACT

Introduction: Unplanned 30-day hospital readmission account for roughly $17 billion in annual Medicare spending. Many factors contribute to unplanned hospital readmissions and multiple models have been developed over the years to predict them. Most researchers have used insurance claims or administrative data to train and operationalize their Readmission Risk Prediction Models (RRPMs). Some RRPM developers have also used electronic health records data; however, using health informatics exchange data has been uncommon among such predictive models and can be beneficial in its ability to provide real-time alerts to providers at the point of care.
Methods: We conducted a semi-systematic review of readmission predictive factors published prior to March 2013. Then, we extracted and merged all significant variables listed in those articles for RRPMs. Finally, we matched these variables with common HL7 messages transmitted by a sample of health information exchange organizations (HIO).
Results: The semi-systematic review resulted in identification of 32 articles and 297 predictive variables. The mapping of these variables with common HL7 segments resulted in an 89.2% total coverage, with the DG1 (diagnosis) segment having the highest coverage of 39.4%. The PID (patient identification) and OBX (observation results) segments cover 13.9% and 9.1% of the variables. Evaluating the same coverage in three sample HIOs showed data incompleteness.
Discussion: HIOs can utilize HL7 messages to develop unique RRPMs for their stakeholders; however, data completeness of exchanged messages should meet certain thresholds. If data quality standards are met by stakeholders, HIOs would be able to provide real-time RRPMs that not only predict intra-hospital readmissions but also inter-hospital cases.
Conclusion: A RRPM derived using HIO data exchanged through may prove to be a useful method to prevent unplanned hospital readmissions. In order for the RRPM derived from HIO data to be effective, hospitals must actively exchange clinical information through the HIO and develop actionable methods that integrate into the workflow of providers to ensure that patients at high-risk for readmission receive the care they need.

1. Introduction

1.1. Importance of preventing hospital readmissions

Unplanned hospital readmissions are vexing events for patients and costly to health care systems across the world. In the United States readmissions are quite prevalent, with one in five Medicare beneficiaries readmitted within 30-days after hospital discharge, accounting for roughly $17 billion in annual spending [1]. Many factors contribute to unplanned readmissions, including: a nascent condition progressing; a recurring exacerbation of a known condition; adverse drug events; premature hospital discharge; and complications or injuries resulting from medical or surgical care [2,3]. Preventing these sentinel events from occurring is critical to patient safety.

Many argue that suboptimal care during index hospitalization or post-discharge may cause preventable readmissions [4,5]. A meta-analysis of studies examining early readmissions concluded that substandard care increased the risk of early readmission by 55% [6]. In an attempt to prevent readmissions, the U.S. Congress included the Hospital Readmissions Reduction Program in the Affordable Care Act, which reduces payments to hospitals with excessive

* Corresponding author.
E-mail address: swain.matthew@gmail.com (M.J. Swain).

http://dx.doi.org/10.1016/j.ijmedinf.2015.09.003
1386-5056/

readmissions for acute myocardial infarction, heart failure, and pneumonia [7]. Since the launch of the program, the Centers for Medicare & Medicaid Services (CMS) has observed a noticeable decrease in readmissions [8].

Despite costs and patient safety issues associated with hospital readmissions, there is a lack of consensus on whether hospital readmission rates are an effective quality measure to assess hospital performance and penalize hospitals for not meeting certain thresholds [9–11]. Joynt and Jha postulate only a small number of readmissions are likely preventable for three reasons: (1) patient- and community-level factors contributing to readmissions are outside the control of hospitals; (2) high readmission rates may be a result of optimal care with hospitals preventing mortality among their most ill patients who made need unplanned follow-up care; and (3) efforts to reduce readmissions may detract care providers from more important quality improvement initiatives [11].

Regardless of whether there is consensus among the health services community on the value of using 30-day hospital readmissions as a quality metric, hospitals are considering various approaches to reduce readmissions among their patient population [12]. In order to maximize benefits to patients across these initiatives, hospitals must be judicious with allocating resources. Most patients are unlikely to be readmitted to hospitals, so investing a large share of available resources in interventions to prevent unplanned readmissions among all patients discharged may be misallocating limited resources. The ability to identify high-risk patients for readmissions prior to discharge would maximize the utility of any intervention aimed at preventing unplanned readmissions, and provide the most vulnerable patients with the care they need.

1.2. Readmission risk prediction models

Identifying patients at risk for readmission is a challenging endeavor. Some researchers have developed readmission risk prediction models (RRPM) to identify high-risk patients [13]. RRPMs employ statistical methods to clinical or non-clinical datasets to identify characteristics of high-risk patients for readmission. Developers of most RRPMs have used administrative [14,15] and claims data [16,17]. These models often leverage demographics, diagnostic information, utilization factors, socioeconomic information, medications, and laboratory test results to predict avoidable readmissions. Developers of these prediction models use available data sources to derive their models, but these data sources may lack meaningful elements that would increase the predictive power.

Understanding predictors of readmission is only the first step in preventing readmissions. Rigby and colleagues suggested that a key issue for addressing the big data challenges for smart health systems and society is developing efficient databases, user interfaces, and tailored search tools to allow access to appropriate data at the point of care [18]. Additionally, hospitals need to consider how the alert derived from the RRPM fits into the workflow of their providers and care teams [19,20]. Even if an RRPM identifies high-risk patients, hospitals need to develop solutions that address issues related to patient hand-offs [21,22] . Any intervention to prevent readmissions must be feasible for all parties and overcome institutional, cultural, financial, and technical barriers to achieve success.

Hospitals often need to know which patients are high-risk for readmission well before the patient is discharged from the hospital; otherwise, the model will have limited value. Using retrospective data sources to construct a predictive model limits the utility of such a model in a clinical setting, as providers cannot incorporate the data into their workflow [23]. Real-time decision support to providers and discharge coordinators flagging high-risk patients during their workflow would enable them to develop a comprehensive care plan or intervention to prevent an unplanned readmission from occurring. One potential data source to facilitate real-time decision support is electronic transaction data transmitted through health information organizations (HIO) [24].

1.3. The role of health information exchange (HIE)

HIOs are entities that facilitate electronic health information exchange (HIE) in a local area [25]. HIOs may support the exchange of admissions, discharge, and transfer (ADT) data, laboratory test results, medication prescribing, public health surveillance data, and care summary records. A real-time algorithm capable of extracting key data elements from these clinical transactions may prove invaluable in preventing readmissions.

The passage of the Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009 provided each U.S. state and territory with cooperative agreement awards to build the capacity for exchanging health information across the health care system both within and across states [26]. In 2012, thirty percent of hospitals and ten percent of ambulatory practices participated in one of the 119 operational health information organizations across the U.S. [27]. Furthermore, three-quarters of U.S. hospitals share data with hospitals and providers outside of their organizations—an eight-five percent increase since 2008 [28]. With more hospitals engaging in health information exchange, there is an opportunity to use these data for population health analytics [29].

Electronic health record (EHR) technology must demonstrate the functionality of transmitting Health Level 7 (HL7) messages as a criterion for certification under Stage 2 the Medicare and Medicaid EHR Incentives Programs [30]. HL7 is a common messaging standard used to electronically exchange clinical data. The standard contains various message types that contain different segments for diagnosis, discharge location, admission type (*e.g.*, accident, emergency), and insurance type, among others. These message segments are capable of leveraging established vocabulary standards. For example, the ICD-9 and ICD-10 (international classification of diseases) codes are often used to code the diagnosis segment, and LOINC (logical observation identifiers names and codes) can be used to encode laboratory results. These machine-readable codes can then be translated to a human-readable form to assist providers with patient care. Among various HL7 message types, ADT messages are commonly exchanged information with HIOs, informing hospitals, physicians, and other trusted caregivers about admission, discharge and transmission of patients in real time [31,32].

The objective of this manuscript is three-fold. The first objective is to identify key predictors of readmission. To address this component, a review of original peer-reviewed studies examining factors associated with 30-day readmissions was conducted to identify the strongest and most common predictive factors of 30-day hospital readmission. The second objective is to ascertain whether developers of RRPMs should consider HL7HIE transactions as a valid data source. Predictors of readmissions extracted from the literature review were mapped to data segments included in HL7 message segments, including ADT messages as well as other message types. The third objective of this study is to investigate the availability and completeness of these RRPM-targeted HL7 segments in three HIO cases.

2. Methods

2.1. Objective 1: review of the readmission predictive factors

An in-depth literature review was conducted in March 2013 using PubMed, Google Scholar, and Embase to identify peer-reviewed articles examining predictors of 30-day hospital