30-DAY HOSPITAL READMISSION PREDICTION MODELS: DESIGN, PERFORMANCE and GENERALIZABILITY

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Abstract

Following the introduction of the Hospital Readmissions Reduction Program (HRRP) in 2012, there has been a push in research and quality improvement efforts to reduce 30-day hospital readmissions. While the needle has moved slightly downward for the high-risk conditions targeted, the majority of hospitals have received some penalty in 2015, totaling over $400 million. Having prediction models for avoidable readmissions would help providers in allocating resources and designing interventions for high-risk individuals. This systematic review searched for peer-reviewed efforts to predict 30-day readmissions published since 1990. In total, 428 articles were assessed for inclusion / exclusion criteria, resulting in 38 articles surviving all criteria. These articles were coded for several factors influencing study design including research setting, data sources, cohort size and characteristics. Further, methodologies were assessed for models implemented, input variable types, validation procedures, and model output and performance. Most studies used electronic medical or administrative records, while a few studies integrated additional data sources such as patient registries and direct patient follow-up. Cohorts varied, with congestive heart failure being the most frequently studied and, surprisingly, only one study developing a combined model for all three conditions originally included in the HRRP. The vast majority of studies used multivariate logistic regression to predict 30-day readmission outcomes, with varied performance. A few efforts were made to include novel statistical methods for readmission prediction, but their ability to improve performance was inconclusive. Unexpectedly, only one study integrated a prediction model into a clinical workflow. The low number of integration efforts could be a result of the difficulty in generating highly accurate models. As the HRRP expands to more conditions, and 30-day readmission gains traction as a quality metric, it is imperative that hospitals are fully informed when deciding which readmission prediction models to implement and when to use them. Several studies suggested model generalizability as a limitation and there were also several key pieces of information missing from some studies. To help assess model generalizability and ensure consistent reporting, this review proposes a modified checklist for 30-day readmission prediction efforts.

Contents

Introduction

In 2012, the Hospital Readmissions Reduction Program (HRRP) was established under the Affordable Care Act, enacting a set of policies to define and measure hospital readmissions for the purposes of penalizing poorly performing hospitals. This program requires the Center of Medicare and Medicaid Services (CMS) to measure readmissions events for a set of specific medical conditions and adjust reimbursements for hospitals participating in the inpatient prospective payment system (IPPS) [1]. The program defines a readmission event as an "admission to a hospital within 30 days of a discharge from the same or another hospital" [1]. Initially, this program intended to reduce unplanned readmissions for three conditions (acute myocardial infarction (AMI), congestive heart failure (CHF) and pneumonia (PNA)). Since its original inception, the list of reportable conditions has been expanded to include chronic obstructive pulmonary disease, elective total hip arthroplasties and total knee arthroplasties. Currently, CMS includes all-cause readmissions for all of the conditions above, meaning that a readmission event is counted towards a hospital's total count regardless of whether the cause was the initial admitting diagnosis.

For each hospital, an "excessive readmission ratio" (ERR) is calculated for each condition, which compares that hospital's readmission rate against the national average. The excessive readmission ratio is risk-adjusted to account for relevant risk factors (e.g. demographics, co-morbidities) that are known to impact an individual's propensity for readmission [1]. Furthermore, CMS uses an algorithm to remove planned admissions from the calculations to avoid inclusion of routine post-discharge follow-ups [2,3]. Currently, poorly performing hospitals can be penalized up to a 3% reduction of reimbursement for all Medicare discharges. In the first year of the program, when the maximum reduction was 1% of

reimbursements, more than 2,000 hospitals accounted for nearly $300 million in financial penalties due to high ERRs [4].

Readmission has been targeted not only because of relatively stagnant historical rates, but also due to of the high associated costs. The risk-adjusted readmission rates for the initial three conditions were stagnant between 2002 and 2009, with PNA and AMI hovering around 18% and CHF around 24% by 2009 [4,5]. A study on Medicare data from 2003 to 2004 calculated that nearly 20% of Medicare patients were readmitted within 30-days with an estimated financial impact of over $17 billion [6]. All-cause Medicare readmissions accounted for $24 billion in total costs in 2011, representing more than half of the $41 billion in total hospital costs for all-cause adult readmission events [7]. The average cost of a Medicare readmission was $13,800 in 2013, which is $700 more than the average cost of an index admission during that same year [8]. Thus, not only is there room for improvement in terms of quality of care and care coordination to improve these relatively unchanged rates, but there is also a significant cost to be captured by reducing readmissions.

Following the introduction of HRRP, Medicare rates of readmission have progressed incrementally. All-cause Medicare readmissions were down to 17.3% by 2013 (compared to 20% for data a decade prior), while the readmission rates for all other forms of coverage (Medicaid, commercial and uninsured) rose between 2009 and 2013 [8]. The readmission rates for all three conditions targeted by HRRP began to drop in 2012, with both PNA and AMI dropping below 18% for the performance time period of July 2010 to June 2013. Congestive heart failure decreased by 2% over three consecutive performance periods, spanning June 2008 to June 2013. However, a significant proportion of hospitals received Medicare reimbursement penalties in 2015 [9]. A total of 78% of hospitals had reimbursement reductions in FY2015 for a

sum of $428 million in penalties [9]. While the total penalties issued, in addition to the proportions of hospitals receiving those penalties, increased in the 3rd year following HRRP, one must note that the penalties are based on a 3-year performance period and there would be a lag for performance improvements to appear in monetary outcomes. Furthermore, the increase in the maximum penalty and number of conditions included in HRRP could influence the upward trend in total financial penalties received by hospitals.

The lack of substantial progress is partially due to the difficulty and cost of implementing readmission reduction programs [10]. A CMS-funded quality improvement initiative implemented in 14 communities only found slight improvements in 30-day readmission rates compared to similar communities, while costing several million dollars to implement [11]. However, with the range of conditions and maximum penalties broadened, there is more incentive to expand quality improvement initiatives, discharge planning and care coordination.

Importantly, not all readmissions are avoidable - a key challenge in the adoption of readmission reduction programs and an argument against the HRRP penalties. In fact, there is much variability published in terms of the proportions of readmissions that are unavoidable. Two studies estimated avoidable readmissions at less than 30% [11]. One systematic review of readmissions studies found that the range of reported avoidable urgent readmissions was between 5% and 78% [12]. These estimates were found to be dependent on the type of patient information used to determine the degree to which a readmission was avoidable. Accurately classifying readmissions as avoidable is crucial for the proper implementation of penalties that are more representative of a hospital's performance, and in the development of methods to intervene on such readmissions. There are many cases in which a readmission cause is preventable, including hospital acquired infections and complications, premature discharge, lack

of medication reconciliation, and poor discharge instructions and planning [13]. However, interventions addressing these cases are costly for the broader population and it could take several years for a hospital to recapture the cost of implementing such programs.

There is a growing demand for solutions to assist hospital systems in controlling readmission rates. Coinciding with the introduction of the HRRP program was the passing of the Health Information Technology for Economic and Clinical Health (HITECH) act in 2009. This legislation established a set of technical specifications surrounding the adoption of Electronic Health Records (EHR), named "Meaningful Use", that hospitals were required to meet in order to receive financial incentives. Since its adoption, the HITECH stimulus has driven the rapid adoption of EHRs in hospitals. By 2014, 97% of non-federal US hospitals had installed a certified EHR, and 75% had a basic EHR system, which includes electronic clinical information, computerized provider order entry and diagnostic results management [14]. This basic EHR adoption is almost a 3-fold increase from 2011 (27.6%), and by 2014 34% of hospitals had comprehensive EHRs, which include decision support tools [14]. The widespread adoption of EHRs could benefit hospitals adopting readmission research and interventions, providing more immediate, accessible and comprehensive patient information during the index admission, while also providing opportunities for clinical decision support.

With the adoption of EHRs, hospitals and providers have the ability to passively search and aggregate patient and population information more efficiently and are more capable of pushing notifications directly to providers during the course of an admission. Having the ability to identify individuals or sets of individuals at higher risk for 30-day readmission would enable providers to divert or increase resources necessary to prevent a readmission. Beyond broad administrative procedures to target avoidable readmissions, hospitals can begin to use

knowledge of specific risk factors for readmissions for highly targeted interventions. Static factors that negatively impact readmission rates such as patient demographics and community factors (e.g. social support and poverty rates) cannot be overcome within the course of an inpatient admission [5]. However, mutable factors, such as medication interactions or blood-glucose levels, can be accessed directly from a medical record, input into a decision model and addressed at discharge or through follow-up.

Other data sources beyond medical records may augment the collection of patient readmission risk factors and provide new opportunities for intervention. Administrative claims data affords the opportunity for more standardized, albeit less expansive, patient data sets across multiple providers. Additionally, technologies such as Health Information Exchanges (HIE), disease registries, and Personal Health Records (PHR) are promising in terms of their ability to improve care coordination, medical record completeness and communication with patients [15]. While integration of patient data across multiple sources and institutions may be ideal for data record completeness and introduction of novel risk factors, it may also raise the difficulty and cost of implementation for an intervention.

To begin to understand the drivers of readmission, risk-factor analyses have been employed on retrospective data. These analyses have begun to pinpoint common factors in patients who are readmitted, including co-morbidities, the number of prior admissions and social factors such as socioeconomic status [15]. While univariate tests (e.g. descriptive statistics) or bi-variate analyses (e.g. student's t-test, χ-square) can pinpoint patterns of a single risk factor and its relationship with readmission, they do not account for interactions between the large set of a patient's demographic and biological characteristics. Building multi-variate models allows for the inclusion of multiple dependent variables and investigates their combined

influence on a measured outcome. Being able to build highly predictive multi-variate models for 30-day readmission would be of great value not only for hospitals to pinpoint individuals at high-risk, but also for organizations such as CMS to enhance risk-adjustment in their ERR measurements [15].

Given the relatively recent introduction of the HRRP and the evolving landscape of healthcare data storage technologies, it is vital to gain an understanding of the limitations and drivers of success in readmission prediction model building. While the incentives for readmission risk prediction and stratification are clear, there are few examples of successful development and implementation of such models [16]. Factors influencing readmission prediction model performance can be teased apart through collecting detailed information on the study settings, study design and types of models employed. Increasing the sample size of index admissions may provide more accurate models; however, prediction models may be prone to overfitting and should be supplemented with external validation. Additionally, the generalizability of readmission models could be investigated by exploring the types of patient cohorts and data sources used during readmission model creation. This systematic review surveyed published prediction models for 30-day readmission to understand the study factors that influenced model development, performance and generalizability.

Methods

Sources

In June 2014, the PubMed and Google Scholar databases were used to search for scholarly articles relating to 30-day hospital readmission risk prediction. To identify studies which investigated hospital readmission, both sources were searched for article titles that included either terms “hospital readmission” or “rehospitalization.” To further identify articles

relating to readmission risk factors or prediction, these terms were conjoined with titles containing “prediction” or “risk” (see Table 1 for exact queries issued). Both searches were limited to published dates between January 1st, 1990 and June 1st, 2014. A similar search was performed against Google Scholar; however, this query was not constrained to the title of the articles. Google Scholar ranks articles by relevance to the search terms, and manual inspection of the articles found that after the 140th ranked article, articles were not relevant to the topic. Additionally, all articles selected were printed in English in peer-reviewed journals. Article citations were downloaded and managed through Zotero, an open-source reference manager.

Recent changes in reimbursement structure and a shift in focus towards outcomes-based care are associated with an increase in research related to hospital readmission. In order to ensure the most recent research was included in the current study, a further search query was conducted in October 2015 for articles published since June 1st, 2014, returning an additional 191 articles after duplicate removal. Again, manual inspection of articles was used to determine the limit of articles obtained through Google Scholar. The second search returned an additional 191 articles after duplicate removal.

To ensure all articles relating to hospital readmission risk models were captured, articles that were not found in the search results but were contained in the final list of the systematic review by Kansagara et al. were included. This resulted in 12 additional articles added to the inclusion / exclusion criteria filtering stage. The failure to identify these 12 additional articles may be a result of search terms being too specific or limitations of the Google Scholar relevancy algorithm.

Table 1: List of sources used, queries executed on sources and resulting article count.

Source	Query	Date Range	Articles
PubMed	(((hospital[Title] AND readmission[Title]) OR (rehospitalization[Title])) AND (prediction[Title] OR risk[Title]))	1/1/1990-6/1/2014	136
		6/1/2014-10/1/2015	38
Google Scholar	(hospital readmission OR rehospitalization) AND (risk OR prediction)	1/1/1990-6/1/2014	140
		6/1/2014-10/1/2015	170
Systematic Reviews			12

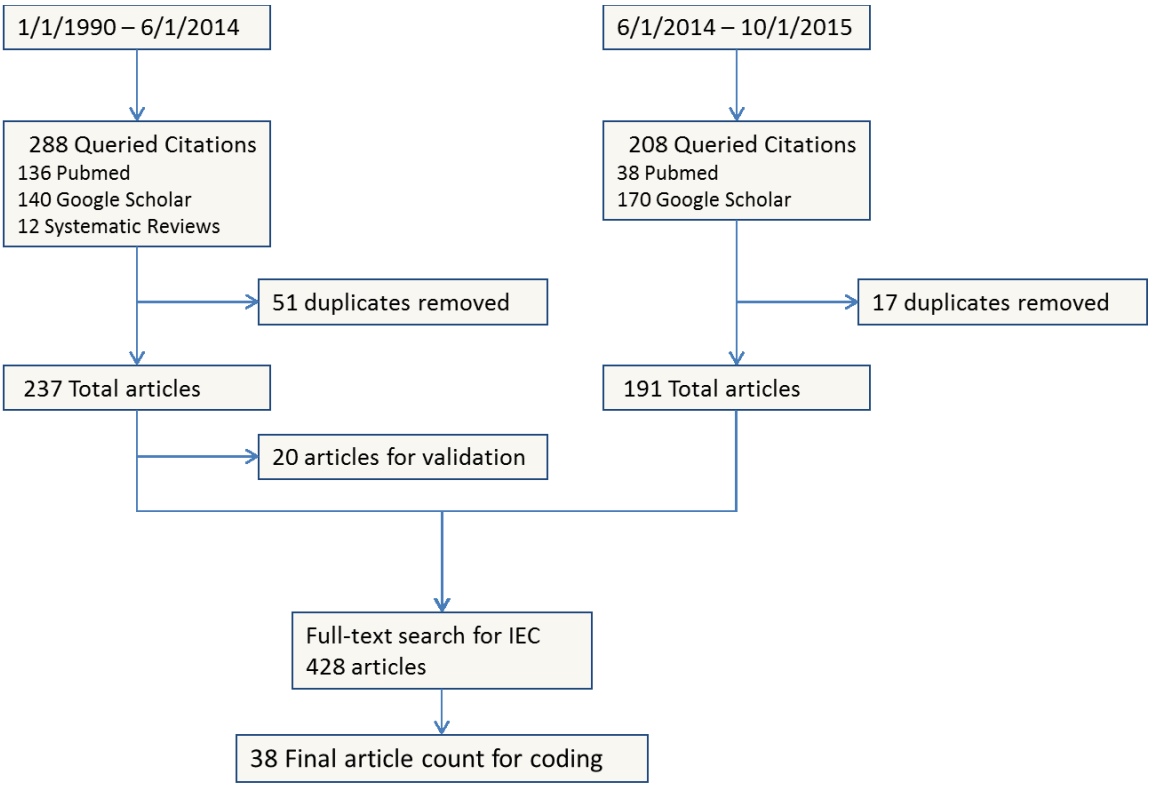
Inclusion/Exclusion Criteria

Inclusion and exclusion criteria (see Appendix IEC) were determined through an abstract review, or a full-text review when abstracts were insufficient. Studies were included if they measured a readmission event using a time-frame defined as within 30-days, 1 month or 28-days post-discharge. This inclusion was used to most closely approximate the 30-day time window used for CMS reimbursement adjustment. As this study was mainly focused on the methods of readmission prediction, articles from outside the United States, or containing non-US data, were included. Systematic reviews and meta-analyses, editorial or abstract-only articles, and studies limited to pediatric groups, defined as cohorts under 18 years old, were excluded. Finally, only articles that built and/or tested a prediction model for hospital readmission were included. For the purposes of this review, prediction models were defined as an analytic method using a set of variables relating to the patient and outputting a probability or prediction that the patient would have an unplanned admission after discharge.

To ensure inter-rater reliability, a subset of the articles was selected for IEC assessment by a researcher blind to the assessments of the other individual (Figure 1). Any discrepancies between the reviewers on individual criteria were resolved through discussion between the two

reviewers. The full list of criteria was updated based on the clarifications discussed by the reviewers. All articles included in the coding stage met the all of the inclusion / exclusion criteria listed above. Following article coding, another researcher sampled the coding results to check for errors and validate criteria.

Figure 1: Literature Flow chart describing source querying and inclusion / exclusion process



Article Coding

To further characterize hospital readmission studies, 17 unique factors were coded (see Table 2). These factors were classified into four categories, including research context, study sample, methodology and model evaluation. To describe the research context, the general characteristics of the study setting and design were coded, specifically whether the study data was derived from academic or non-academic hospital contexts (or other contexts, such as health information exchanges or patient registries), and the size of the hospital network if available.

The existence of any data sources listed in the article was also recorded, as well as if the source was in electronic form, if noted in the article. In particular, it was noted whether the readmission-related data was extracted from a medical record (e.g. patient charts or EHR), administrative records, surveys or other sources. These were deemed important to assess the ease of implementation and generalizability of the model to other settings.

Under the study sample, population attributes were recorded, including general inclusion and exclusion criteria into the study cohort, the type of cohort used and the sample size. Sample size was calculated as the sum of distinct index admissions used in all models and cohorts (e.g. derivation and validation). The type of cohort ranged from an all-cause readmission prediction model to models predicting readmission in patients with specific conditions, undergoing surgical procedures, within a specific age range or any other cohort definition provided.

Table 2: List of Categories and Factors used to Code Hospital Readmission Studies

Category	Factors
Research Context	Study setting
	Data source & description
	Number of hospitals within network
	Outcome measured (readmission window)
	Type of study (retrospective vs. prospective)
	Data sources
	Specific technologies listed
Study Sample	Population sample size
	General inclusion / exclusion
	Type of cohort
Methodology	Types of variables included in model
	Analytical models used
	Existence of derivation / validation Sets
Model Evaluation	Model output

	Model accuracy
	Important factors discovered
	Implementation into workflow

Due to a wide variety of factors that could influence readmissions for different cohorts, the variables tested were characterized into categories, rather than using the specific variables themselves. Categories for model input included demographic, social, diagnostic, procedural, laboratory, behavioral, mental status, hospital resource utilization, history, vitals, and various indexes. Descriptions and examples of each category can be found within Table 3. All analytical models used in each study that intended to predict readmission risk were recorded. Categories for methods included bi-variate analysis (which focused on a single variable's impact on readmission odds, often used to identify variables for inclusion in a multi-variate model), multi-variate logistic regression, Cox proportional hazards, or other analyses (e.g. Support Vector Machines, Bayesian networks). The existence of model training or testing was coded, whether executed through internal validation methods like bootstrapping, sample splitting or external validation. The sample split percentages were also recorded.

Table 3: Readmission prediction model input categories, with descriptions and examples

Model Input Variable Category	Category Description	Examples
Demographic	Traditional demographic factors	Age, gender, ethnicity
Social	Socioeconomic factors beyond those typically collected upon admission	Social support, impoverished, residence distance to hospital
Diagnostic	The presence of a primary diagnosis and / or co-morbidities	ICD-9/10 codes, diagnostic categories, co-morbidities
Procedure	The occurrence of a surgical procedure during the index admission and any resulting complications	CPT codes, occurrence of a general procedure, procedure complications

Laboratory	Any laboratory codes, results or a cumulative number of tests during index admission	Albumin, Hbac1, GFR, BUN
Indexes	Composite scores compiled from patient information	Charlson Co-morbidity Index, ASA Class, Elixhauser Co-morbidity Index
Vitals	Vital sign measurements collected during the index admission	BMI, blood pressure, respiratory rate, blood oxygenation
Medications	Presence of specific medications, types of medications or the total number of medications the patient is treated with	
Medical History	Any non-diagnostic information describing the patient prior to the index admission	
Length of Stay	The length of the patient's inpatient stay, from admission to discharge	
Discharge Location	The location / type of facility where the patient is discharged	Home, long-term care
Behavioral / Cognitive	Any information describing the patient's mental state or social behaviors exhibited	Smoking, alcohol use, depression symptoms
Resource Utilization	Variables representing the use of healthcare resources within a period prior to the index admission and up to discharge	Number of admissions within past year, ER admission within 30 days, number of consultations
Hospital Characteristics	Information describing the hospital or hospital system	Complexity of hospital system, number of beds, bed occupancy
Other	Any other information that does not fit into the other categories	Functional status, discharge season, admission urgency

The final category used to code hospital readmission risk models was model evaluation. The model output was coded in terms of the statistic or risk stratification measurement. The model accuracy was also coded in terms of the significance threshold used for the input variables and / or the performance of any models included in the study (e.g., the c-statistic). This

information was used to gauge the model performance. Any risk factors that were specifically noted, had reached statistical significance, or had been included in the final model were recorded.

Finally, to assess the practicality of the model, any specific technologies relating to data extraction, data storage or specific algorithms used were noted. This could include a specific EHR brand, or a type of clinical database (e.g. clinical data warehouse). It was noted whether the model was implemented into operating clinical workflow, including the methodology of implementation. Any specific limitations noted by the authors were also recorded.

Results

Study and Data Context

In total, 38 peer-reviewed studies were found to have tested or included a prediction model for 30-day hospital readmission. A total of 15 studies were held in academic hospital environments (Table 4) [17-31]. These studies included an average of 1.8 hospitals in their readmission data, with a mean sample size of 15,278 index admissions. There were 10 studies held in non-academic hospital environments, which contained an average of 24.3 hospitals and 270,560 index admissions [32-41]. The largest sample was held in a non-academic environment and contained over 2.3 million index admissions across 41 hospitals in Hong Kong [36]. The smallest sample was 100 patients who were enrolled in a tele-monitoring program post-discharge [18]. Four of the studies included a combination of both academic and non-academic hospitals in their data, with an average of 18 hospitals (this average was driven by a study held in Switzerland containing 49 acute care hospitals) [42-45].

A total of 9 studies were conducted outside of hospital environments [46-54]. These studies used various claims databases (e.g. Medicare claims), and patients registries (e.g.

Quebec Trauma Registry, American Heart Association's Get with the Guidelines-Heart Failure registry, New York State Cardiac Surgery Reporting System). In all but two of these studies, the number of hospitals from which the data originated was not specified [48,52]. For studies with regional or national registry data, the data can be sourced from several hundred hospitals, such as the case with the National Surgery Quality Improvement Program which includes up to 400 hospitals [50,53]. Given the broad scale of data collection for patient registries and insurance providers, the average sample size was substantial, with over 100,000 index admissions. The smallest sample size in this study setting group contained 6,615 index admissions, while the remaining studies conducted outside hospital environments had more than 16,000 admissions each.

Table 4: Readmission study setting count with sample sizes and data source combinations

		Hospital Readmission Study Setting					
		Academic	Non-academic	Both Academic and Non-Academic	Other		
	Citations	17,18,19,20,21,22,23,24,25,26,27,28,29,30,31	32,33,34,35,36,37,38,39,40,41	42,43,44,45	46,47,48,49,50,51,52,53,54		
	Avg. Number of Hospitals	1.8	24.25	18.25	45.5		
	Avg. Sample Size	15,278	270,560	50,568	102,134		
	Smallest Sample	100	189	26,045	6,615		
	Largest Sample	118,221	2,344,003	131,809	628,929	**Total**	**Percent**
Data Source Combination	Medical Only	6	2	2	0	10	26.3%
	Medical and Survey	1	0	0	0	1	2.6%
	Medical and Other	0	1	0	0	1	2.6%
	Administrative Only	2	2	1	1	6	15.8%
	Administrative and Survey	1	0	0	0	1	2.6%
	Administrative and Other	0	0	0	4	4	10.5%
	Medical and Administrative	4	3	0	2	9	23.7%
	Medical, Administrative and Survey	0	0	1	0	1	2.6%
	Medical, Administrative and Other	1	2	0	0	3	7.9%
	Other only	0	0	0	2	2	5.3%
	Total	15	10	4	9		
	Percent	39.5%	26.3%	10.5%	23.7%		

Data Sources

Medical and administrative data sources were the most prevalent source types across all 38 studies, and most were stored in electronic form; however, this could not be ascertained for some studies. In total, 24 medical sources and 24 administrative sources were used to collect readmission data (Table 5). Ten studies collected data using sources other than medical and administrative records, and 3 studies used survey techniques to collect data including telephone follow-up and patient interviews [20,29,42]. The most frequent data source combination was medical records only (26.3% of studies), followed by medical and administrative records (23.7%) and administrative records only (15.8%). Two studies used only *other* data sources (those that did not fit into the medical or administrative classification), while 4 studies used a combination of three sources, including medical, administrative and either *other* or survey (Table 4). Most of the data sources (81%) were in electronic form where applicable, however, one medical record was not in electronic form [34] (Table 5). Importantly, for 10 individual data sources it could not be determined whether the source was electronic or not. In some cases, the specific technology used for the data source was mentioned, such as Epic EHR [17,43] or system-wide electronic data warehouses [21,25]. Interestingly, one study included data source as a factor and considered the effect of the various combinations of data sources, and the variables derived from these sources, on the performance of readmission risk models [30].

Table 5: Data sources used including the mode of storage

Citations	Data Source Type	Data Source: Electronic	Citations	Data Source: Not Electronic	Citations	Data Source: Not Specified	Citations	Total
17,18,19,22,23,24,26,27,28,29,30,31,42,43,45,32,34,35,36,37,38,39,40,46,47	Medical	19	17,18,19,23,26,27,30,31,43,45,32,35,36,37,38,39,40,46,47	1	34	4	22,28,29,42	24
19,20,21,22,25,28,30,31,42,44,33,35,36,37,38,39,41,46,47,48,49,51,52,54	Administrative	19	19,21,25,30,42,44,35,36,37,38,39,41,46,47,48,49,51,52,54	0		5	20,22,28,31,33	24
28,37,39,40,48,50,51,52,53,54	Other	9	37,39,40,48,50,51,52,53,54	0		1	28	10
20,29,42	Survey	3	30-day follow-up, Telephone follow up, Patient interview					

Study Samples

There were several categories of patient cohort types used for data inclusion and model development, with CHF being the most frequent medical condition included. These cohort types included all-cause (found in 17 studies), one condition (12) or groups of conditions (3), age restriction (9), surgical procedures (5) and *other* restrictions (9) (Table 6). Single conditions applied alone included CHF (7 studies), ischemic stroke, type-2 diabetes and cancer. One study applied all three conditions first targeted by HRRP (CHF, AMI and PNA), while another study applied a group of 12 high-volume conditions [19,49]. All age-restricted studies used a cut-off of 65 years old, which is the starting age of eligibility for Medicare. Surgical procedures used to define cohorts included cardiac procedures, hysterectomy, thyroidectomy and allogenic hematopoietic cell transplantations (allo-HCT). The most frequent cohort that fit into the *other* category was the inclusion of the veteran population [33,37,38,41]. Additional restrictions in this category included trauma patients, patients on parenteral antibiotic treatments, patients who used an otolaryngology service, and patients who filled a prescription following discharge.

Cohort types were either applied alone or in combination with other types, producing 15 distinct total categories. Studies that focused on all-cause models exclusively were the most

frequent combination (9), while there were 3 studies that combined all-cause with an age restriction. Four studies that used an age restriction also focused on one condition and one study used an age-restriction with a group of conditions. All-cause and age-restriction combined models had an average of nearly 800,000 index admissions; however, this average was heavily driven by one study with over 2.3 million admissions (another study in this category had only 183 admissions). The average number of input variable categories used in readmission models varied across all the cohort combinations, ranging from 4 to 8 categories (Table 6). The study with 8 input variable categories was an extensive investigation of readmission, developing several models with various cohorts and data source combination and including 118,000 index admissions [30].

Table 6: Cohorts used in models, with average sample sizes and input variable category counts

Cohort Type	Includes Cohort (Not Exclusively)	Citations	Includes Cohort (Exclusively)	Citations	Avg. # Variable Categories	Avg. Sample Size	Description
All-Cause	17	20,21,22,25,29,30,42,43,44,45,32,33,35,36,39,41,47	9	20,22,42,43,44,45,32,35,39	6.9	43,278	
One Condition	12	17,18,21,24,28,30,31,37,40,46,51,54	4	17,18,28,40	6	13,770	7 CHF; 1 ischemic stroke; 1 Type-2 diabetes; 1 cancer
Age-Restriction	9	25,29,31,36,38,46,49,51,54	0				Greater than 65 years old
Group of Conditions	3	19,34,49	2	19,34	6.5	2,957	CHF, AMI and PNA; Pyschiatric; 12 high-volume conditions
Surgery	5	24,26,50,52,53	4	26,50,52,53	6.8	23,554	2 cardiac; 1 hysterectomy; 1 thyroidectomy; 1 allo-hct
Other	9	23,27,30,33,37,38,41,47,48	3	23,27,48	7	19,860	4 veteran; 1 trauma; 1 patients who picked up prescriptions; 1 patients who had antibiotic treatment; 1 population that used otolaryngology service; 1 model that focused on data source combinations
All-Cause & One Condition			1	21	6	46,209	
All-Cause, One Condition & Other			1	30	8	118,221	
All-Cause & Other			3	33,41,47	4	5,382	
All-Cause & Age-Restriction			3	25,29,36	5.3	791,159	
Age-Restriction & One Condition			4	31,46,51,54	5.3	171,242	
Age-Restriction & Group of Conditions			1	49	4	6,615	
Age-Restriction & Other			1	38	7	129,400	
One Condition & Other			1	37	8	3,436	
One Condition & Surgery			1	24	5.0	618	

Model Inputs

Studies including medical record data tended to include more input variable categories in the prediction model development. Models that utilized only medical record data sources used 6.2 input variable categories on average, while those using only administrative sources had

an average of 4.5 categories (Table 7). Studies that used both medical record and administrative data sources also input an average of 6.2 input variable categories into their models. Two data source categories (medical and *other* and *other* only) had the highest number of input variable categories with an average of 9, while three studies using medical administrative and *other* sources used 8.7. Two studies used 11 of the variable categories [32,53] and conversely, one study used just the Diagnostic category [18]. One study included an Index (LACE[1]) and Resource Utilization variables, and another used just Demographic and Diagnostic input data ([42,47], see Table 3 for description of categories).

Table 7: Counts of data source combinations with average input variable categories

Citations	Data Source Combination	Combination Count	Avg. # Variable Categories
17,18,23,24,26,27, 43,45,32,34	Medical Only	10	6.2
29	Medical and Survey	1	6.0
40	Medical and Other	1	9.0
21,25,44,33,41,49	Administrative Only	6	4.5
20	Administrative and Survey	1	4.0
48,51,52,54	Administrative and Other	4	6.0
19,22,30,31,35,36, 38,46,47	Medical and Administrative	9	6.2
42	Medical, Administrative and Survey	1	2.0
28,37,39	Medical, Administrative and Other	3	8.7
50,53	Other only	2	9.0

[1] LACE is a composite measure that includes the length of stay, whether the admission was acute, the Charlson co-morbidity index score, and the number of visits to the ER in the prior 6 months

Variables that are typically easier to access were more commonly represented in models, including Demographics, appearing in 35 studies, Diagnostic (32), and Resource Utilization (23) (Table 8). The Resource Utilization input variables most common were the count of emergency visits or general admissions within a specific time period prior to the index admission, frequently 6 months to a year. Twenty-two studies used Indexes, of which the most frequently used were the Charlson co-morbidity index, LACE and the Elixhauser co-morbidity index. Less frequent indexes included the American Society of Anesthesiologists (ASA) physical status classification system, Injury Severity Score, Acute Physiology and Chronic Health Evaluation (APACHE), Brief Psychiatric Rating Scale (BPRS), New York Heart Association Functional Classification for Heart Failure, Tabek Mortality Score and the High-Risk Diagnoses for the Elderly Scale.

Table 8: Model input variable categories and counts

Variable Category	Variable Category Count	Citations
Demographics	35	17,19,20,21,22,23,24,25,26, 27,28,29,30,31,43,45,32,33, 34,35,36,37,38,39,40,41,46, 47,48,49,50,51,52,53,54
Diagnostic	32	17,18,19,21,22,23,24,26,27, 29,30,31,43,45,32,33,34,35, 36,37,39,40,41,46,47,48,49, 50,51,52,53,54
Resource utilization	23	17,19,20,21,22,23,25,27,30, 42,43,44,45,32,34,35,36,37, 38,39,40,48,54
Indexes	22	17,19,20,23,24,25,28,29,42, 43,44,45,33,34,35,37,38,39, 40,48,50,53
Social	19	17,19,20,21,22,23,25,28,29, 30,43,32,33,35,36,37,38,39, 41
Procedure	14	21,22,24,26,27,45,32,33,40, 49,50,51,52,53
Laboratory	14	19,22,28,30,31,43,32,39,40, 46,50,51,53,54
LOS	14	19,21,22,23,27,29,43,32,35, 40,41,49,52,53
Other	13	22,28,29,30,45,34,35,37,38, 39,48,50,53
History	11	23,24,27,28,31,32,36,51,52, 53,54
Vitals	10	28,31,43,32,37,39,50,51,53, 54
Medications	10	19,22,23,28,32,35,38,39,40, 53
Discharge Location	10	23,25,27,30,45,32,33,35,40, 53
Behavioral/Cognitive	4	17,30,37,39
Hospital Characteristics	3	38,52,54

Less frequently included variable categories were Social (19 studies), Procedure (14), Laboratory (14), *Other* (13) and Discharge Location (13). Less than half of models used Length of

Stay (14), which was surprising given the relative simplicity of the calculation and its widespread use as a quality indicator. Common Social variables were marital status, social support, caregiver status, living situation upon discharge, and socioeconomic status. A few studies included geographic data to determine whether distance to the hospital or remoteness of residence influenced risk of readmission. Procedures were represented by number and type of procedure, with some studies noting procedure complications and one study using all CPT codes associated with the patient's index admission. Typical Laboratory values included were albumin, hematocrit (HCT), blood urea nitrogen (BUN), plasma sodium, hemoglobin, glomerular filtration rate (GFR), and creatinine. The most frequent *Other* variables were comprised of functional status (4), Activities of Daily Living (2), discharge season (2), disability status, fragility-related diagnoses, type and source of admission, admission urgency, term frequency-inverse document frequency from clinical notes, body region and mechanism of injury for trauma patients, episodes of seclusion or restraint for psychiatric cases, and imaging results. The use of term-frequency inverse-document frequency was used by one study for text mining of clinical notes to isolate important keywords, such as those relating to a substance abuse (e.g. "abuse", "dependence", "withdrawal") and potentially identifying behavioral risk factors [30]. Behavioral / Cognitive risk factors were included in four studies and consisted of noted substance abuse issues as well as an estimation of high risk behaviors from visits to a social worker or presence of an STD.

Models Used

The vast majority of studies used multivariate models for 30-day readmission prediction with all but two studies including a multivariate logistic regression in their study (Table 9). Twelve studies used only a multivariate model, and 18 studies conducted both a bivariate and multivariate analysis. Less frequent analysis combinations included multivariate, bivariate and *other* (4), multivariate and *other* (2), bivariate only (1), and *other* only (1). The bivariate only

analysis was conducted on a previously validated index (LACE) while the *other* only study also tested the accuracy (using a Receiver Operating Characteristic, or ROC, analysis) of three previously validated screening tools [29,44].

Importantly, 7 studies used a model, or set of models, other than bivariate or multivariate. *Other* models included support vector machines and the SQLApe (Striving for Quality Level and Analyzing of Patient Expenses) algorithm to identify and eliminate admissions that were unavoidable [22,30]. A custom model was built using elements of hazard models, Bayesian networks and Markov Chain Monte Carlo models and subsequently compared to a multivariate logistic model [41]. In addition to a multivariate logistic model, one study used classification and regression trees (CART), C5. 0 and Chi-square Automatic Interaction Detection (CHAID), and neural networks models [39].

Table 9: Models used for readmission risk prediction with model outputs, validation methods and validation size where appropriate.

Citations	Model Combinations	Model Combination Count	Model Outputs	Model Validation Methods	Average Validation Cohort Size (% total sample)
44	Bivariate Only	1	Relative Risk(1)	Not applicable(1)	Not applicable
18,20,42,45,32,33,36,46,47,48,49,54	Multivariate Only	12	Odds Ratio(9), P-value(11), C-statistic (11), Relative Risk(1), Other(3)	None(1), Derivation / Validation(9), Bootstrapping(1), Not applicable(1)	0.431
17,19,21,23,24,25,26,27,28,31,34,35,38,40,50,51,52,53	Bivariate and Multivariate	18	Odds Ratio(12), P-value(15), C-statistic (16), Relative Risk(1), Other(5)	None(4), Derivation / Validation(6), Bootstrapping(5), Not applicable(3)	0.332
30,41	Multivariate and Other	2	C-statistic (1), Other(1)	Derivation / Validation(2)	0.3
29	Other	1	C-statistic (1)	Not applicable(1)	Not applicable
22,43,37,39	Multivariate, Bivariate and Other	4	Odds Ratio(4), P-value(4), C-statistic (4), Other(4)	None(1), Derivation / Validation(3)	0.387

Model Outputs and Validation

Nearly all studies that included a multivariate logistic regression model also included a model output of the c-statistic (Table 9). The c-statistic, equivalent to the ROC or area-under-curve (AUC), is a measure of a model's performance compared with the alternative of the model performing at chance (AUC of 0.5). The majority of models also provided p-values and odds ratios or relative risks when reporting the significance of individual factors in the models. Six of the studies stratified the model output into a risk score or level, indicating an individual's level of risk for a 30-day readmission [17,20,22,31,39,54]. One study output the mean-square error for a custom model and compared this to other models tested (including BayesNet, CART and a machine learning algorithm, AdaBoost) [41].

For model validation, 20 studies used a derivation / validation sample splitting technique with an average of 40% of the source samples used for validation (Table 9). Four of these studies also used external data for validation [21,28,32,42]. Six studies used bootstrapping techniques to validate models, using between 200 and 500 random samples. In six cases there was no evidence of validation of models where applicable. In two studies, integrated discrimination improvement and net reclassification improvement were used for model comparison [37,43].

Model Accuracy

Model performance was highly variable across studies, depending on the type of cohort included, model type and input variable combination. Two studies that focused on all-cause index admissions and readmissions with an age restriction produced relatively underperforming models, with c-statistics less than or equal to 0.65 ([25,29], Table A1 in Appendix). Conversely, one study with the same inclusion criteria had promising results, yielding a c-statistic of 0.819 for the derivation set and 0.824 for the validation. This study used less input variable categories than the other two studies; however, it also included far more samples, most likely contributing to its discriminative capacity (2.3 million index admissions compared to roughly 30,000 and 183). Studies using only all-cause cohorts had encouraging model performance. Two all-cause models using variables collected upon the index admission or within 24-hours from the time of admission, resulted in c-statistics between 0.69 [43] and 0.76 [32]. Further, the discharge models for these two studies performed slightly better; both including data that would be collected upon discharge (e.g., LOS, discharge location, laboratory values upon discharge). A study that investigated the performance of a previously validated index, LACE, produced c-statistics between 0.711 and 0.774, depending on the index cut-off used and addition of other risk factors [35]. This was similar to another all-cause model, which also used LACE and achieved

c-statistics between 0.68 and 0.71 for the training / testing sets [42]. An all-cause model developed only using an administrative data source produced c-statistics between 0.75 and 0.81 across training sites and testing samples [21].

Models implementing methods other than bivariate analyses and multivariate logistic regression achieved some modest improvements when compared directly against the traditional methods. One study developed an all-cause model achieving a c-statistic of 0.68, but also utilized supervised learning using support vector machine (SVM), producing a c-statistic of 0.74 [30]. A study comparing a custom model to other logistic and non-logistic models found the mean-square error (0.05) to be substantially less than other models (CART, AdaBoost, logistic – 0.16, BayesNet – 0.225) [41]. However, this all-cause model was implemented in a veteran population, a population with unique characteristics. Two models attempted to improve upon CMS 30-day readmission models. One all-cause model demonstrated significant improvement over the CMS model with integrated discrimination improvement ($p < 0.05$) and net reclassification improvement ($p < 0.001$) [43]. Another study, focusing on ischemic stroke in veterans, compared the CMS model (C=0.636) to a model with the CMS input and social factors (C=0.646) and CMS input with both social and clinical factors (C=0.661) [37].

Performance varied among studies attempting to predict readmission risk for one or more conditions. A study found very good discrimination for readmissions due to CHF (C=0.92), procedure complications (C=0.88) and mood disorders (C=0.84), all of which were more accurate than the all-cause model and model for readmissions due to general symptoms [30]. Another model for CHF was fairly accurate for the derivation set (C=0.73), and slightly less for the validation set (C=0.69) [17]. By using both clinical and non-clinical factors in their CHF model, one group was able to achieve a c-statistic of 0.69 [28]. Another study had less accurate CHF

models, whether the model was derived from medical or administrative sources (C=0.58-0.61) [46]. A U.S. group developed a model for Type 2 diabetes, a condition not currently monitored for 30-day readmissions under HRRP, with some success (C=0.69) [40]. The one model derived for three of the HRRP-focused conditions (CHF, AMI and PNA) produced reasonable accuracies for the derivation (C=0.64-0.73) and random sample validation sets (C=0.63-0.76), but performed slightly worse for a historical validation (C=0.61-0.68) [19]. Two studies produced very good discrimination (C=0.83-0.85); however, these studies focused on patients that used an otolaryngology service and those who underwent hysterectomies [27,50]. Finally, a study on chronic pancreatitis built a model with c-statistics between 0.65 and 0.73, depending on the derivation / validation sample and site [21].

Important Factors Discovered

There were several variables that were included in multiple final readmission risk models (Table A1). Basic demographics including age, race and gender were statistically significant in many models, with a higher age increasing the odds of a 30-day readmission in most. Co-morbidities were also a significant risk factor, whether measured through the number of co-morbidities, the presence of high-risk conditions or the Charlson co-morbidity index. Other indexes predictive of readmission included LACE, ASA physical status class, Tabek mortality score, APACHE score, and BPRS for psychiatric patients. Several studies found the number of previous hospitalizations to be an important risk factor for readmission, as well as the length and type (elective vs. emergent) of index admission. Predictive social and behavioral factors included marital status, living alone, poverty levels, distance to hospital (further being less likely in one study [25]), drug use, and the presence of anxiety or depression. One study found hospital characteristics impacted the risk of readmission, including annual surgery volume and hospital risk-adjusted mortality rates [52]. As expected, several clinical factors found were

specific to the cohort included, such as prep regimen for allo-HCT patients, heart failure classification, or a presence of IC9-CM code for radical pancreaticoduodenectomy for chronic pancreatitis patients [21,24,28]. Functional status of the patient and discharge location also played an important role in several models. Finally, there were several laboratory values derived from medical record sources that were predictive of readmission, including BUN, HCT, albumin, sodium and creatinine.

Technologies and Model Implementation

Technologies listed for data storage or extraction included several EHRs, clinical and administrative data repositories and patient registries. Clinical research databases used included Research Electronic Data Capture (RedCAP) and Clinical Investigation Data Exploration Repository (CIDER) [23,27]. Other studies utilized administrative databases, including the Johns Hopkins Casemix Datamart, Ontario administrative databases and Medicare Standard Analytic File [21,42,46]. Several studies extracted data from the hospital system's EHR, in some cases listing the specific brand such as Epic or Cerner [17,32]. Registries for specific conditions or procedures included the Unified Transplant Database at Cleveland Clinic, an EHR-based disease registry, the Quebec trauma registry, the Get with the Guidelines Heart Failure project, the NYS Cardiac Surgery Reporting System and the National Surgical Quality Improvement Program (NSQIP) [24,39,48,51,53]. Following model development, two studies specifically mentioned plans for implementing the model into the clinical workflow [19,21]. Only one study reported model integration into the hospital system [36]. The model was run live as a daily screening tool to identify high-risk elderly patients. Risk scores were computed daily upon discharge and high-risk patients were automatically forwarded to disease management for telephone follow-up.

Study Limitations

Nearly all of the studies explicitly mentioned limitations, with the most often mentioned relating to model generalizability or data completeness. Models may not be completely generalizable due to the specific settings of the hospital (rural vs. metro), unique study populations (e.g., veterans) or unique care delivery systems (e. g. Kaiser Permanente's integrated delivery system). Less frequently captured social, demographic or clinical information led to issues with incomplete records and reduced sample size. Several studies noted that a lack of external validation reduced the generalizability of the model. Further, many studies noted that there was no capability to monitor inter-hospital readmissions due to data systems being segregated and data access limited. Small sample sizes hindered some studies, leading to wide confidence intervals for estimations. A lack of access to extensive clinical data was also mentioned, which could account for some of the uncaptured variance in the models. Finally, one study was conducted in Israel and made specific mention of population and hospital system organizational differences between Israel and the United States [39].

Discussion

With the rollout of Medicare reimbursement adjustments following the introduction of the HRRP, there has been increased pressure on hospital systems to adapt and reform. The possibility remains that the program could extend to other high-risk conditions or similar adjustments could be made for 30-day readmissions in the commercial insurance market. Broad organizational changes, such as increased staffing or resources for discharge, may be effective at reducing admissions; however, they are costly to apply to all index admissions. Thus, a strong case can be made for mechanisms to predict an individual patient's 30-day readmission risk. This systematic review included recent attempts to predict readmission risk.

Out of the 38 studies, there was a wide variety of study settings where readmission prediction models were developed. Having access to a large hospital network not only allows for larger samples, it introduces more opportunity for representing the general population and including less prevalent events into the model. Two studies with over 40 hospitals produced sample sizes of over 130,000 and over 2 million, with promising results [34,43]. While large healthcare organizations, including integrated hospital networks, HIEs and data registries tended to produce larger data sets, there is no guarantee this will lead to more accurate models. A model built with over half a million admissions produced modest results, even when augmenting the administrative data with medical records [44].

The majority of studies included medical or administrative sources for readmission data; however, only a third of studies included both. Incorporating medical sources provides the advantage of recently collected data and proximity to the care providers through the EHR. Further, studies utilizing medical records tended to have more input variable categories in their models, demonstrating the relative richness of EHR data. Several studies listed a lack of access to clinical variables as a limitation to their work. Using medical sources provides the ability to isolate variables within an EHR that are predictive of readmission and potentially incorporate models into clinical decision support systems. This would allow risk scores to be computed in the background and notifications to be generated during the course of the index admission or prior to discharge. However, this may come at a cost of data quality and incompleteness, also noted by several studies in their limitations. Several advantages exist for administration data, including the cleaning and standardization of data for billing or quality improvement purposes. Further, isolating model input data that adheres to common terminologies could lead to easier integration across study sites.

Several studies used patient registries and HIEs to collect data, while three studies used surveys for patient follow-up. These sources may allow for a more complete and longitudinal patient record, spanning across multiple institutions. However, implementation using registries and HIEs would require integration and fast communication with outside sources for operation within the index admission. Surveys could allow for patient-reported outcomes but are also costly to implement when not automated, and are difficult to conduct on a large-scale for research. Thus, it is imperative for individuals on the academic research and operations side to weigh the costs and benefits of including multiple data sources when available.

There was a wide range of cohort restrictions for prediction model development, only a minority of which fit the given range of conditions and age-restriction of HRRP. This suggests that organizations view 30-day readmission as an important quality metric for other non-regulated cohort combinations. Seven studies used a CHF diagnosis for inclusion while two included patients who underwent cardiac surgery. The popularity of such models is most likely driven by the high rate of readmission and prevalence of CHF. Surprisingly, only one study included all three conditions originally covered under HRRP (CHF, AMI and PNA) into a combined model [19]. While this study developed both condition-specific models and a combined model, there was no direct statistical comparison to determine if the combined model had less accuracy. Further research is needed to explore the accuracy and ease of implementation of disease-specific readmission prediction models against all-cause. Finally, caution must also be taken when interpreting and potentially incorporating models, considering that certain cohorts may have had unique characteristics. For instance, all-cause models stemming from veteran populations would be built primarily on males who are more economically deprived [38]. Further, it is important for authors of studies investigating readmission prediction models to

describe in detail sample demographics and note any unique features of the community where most of the study population resides.

Nearly all of the studies used a multivariate logistic regression for development of a prediction model. Only three studies included additional modeling techniques, including support vector machines and Bayesian networks. While there was insufficient evidence for additional value provided by these methods, advanced methods like supervised learning and artificial neural networks have shown promise in disease prediction [55-57]. Further, implementing naïve approaches or well-defined heuristics for feature selection may uncover new predictors of interest and would increase the reproducibility of model deployment [21]. Future readmission prediction research should consider developing non-traditional classifiers, comparing them against traditional models such as logistic regression.

Model validation is necessary to demonstrate generalizability and reproducibility. Most studies used model validation when appropriate, either through internal bootstrapping or by sample splitting. External validation is also imperative regardless of the model validation technique, and only a few studies were tested against external data. One group was able to validate their model on a database of 1 million admissions, finding very similar model performance to the internal derivation and validation sets [42]. External validation would serve to determine if population differences between hospital systems are similar enough for model adoption. Further, deploying a model at an external site would test the data coverage for model inputs and the ease of model implementation. Only one study mentioned successful implementation of a model into clinical workflow post validation and further work is required to test and report on implementation efforts for other models [36].

The most common limitation listed among the studies was the concern over reproducibility of the prediction model. While model validation can be used to test generalizability, documentation of the various elements described in this study would be critical for and expedite predictive model implementation decisions. For instance, when reporting data sources used for readmission research, the mode of storage and collection should be explicitly noted, as well as any specific technologies used. Ten studies did not explicitly report whether the source was electronic, and the majority of studies failed to note the specific technologies (e.g., brand of EMR or clinical data repository) from which the data was extracted. Additionally, while models incorporating multiple data source types could be more accurate and appealing, they may also be more difficult to implement, possibly requiring data integration and alignment across disparate systems (e.g., connecting to a patient registry or HIE in near-real time to check a patient's medication history). Reporting and elaborating on data context for generalizability determination should also be extended to cohort selection.

Finally, having a consistent framework for conducting and reporting readmission risk prediction efforts would help in the preparation and the assessment of such research. A number of frameworks do exist for the development of prediction models for medical diagnoses, but these frameworks need to be extended for 30-day readmission. Specifically, both the Critical Appraisal and Data Extraction for Systematic Reviews of Prediction Modelling Studies (CHARMS) and the Transparent Reporting of a multivariate prediction model for Individual Prognosis or Diagnosis (TRIPOD) provide guidelines for reviewing and reporting on diagnostic / prognostic prediction models [58,59]. The TRIPOD framework could be extended for 30-day readmission prediction studies to include checklist items including: data source types; data source integration efforts; filtering of unplanned or unavoidable readmissions; relevant community characteristics; model performance compared against standard models (e.g. CMS); detailed

implementation efforts with challenges, successes and lessons learned; and finally, specific technologies utilized (see Table 10).

Table 10. TRIPOD adaptation for 30-day readmission prediction studies (modifications are bolded, italicized and red).

Checklist of Items to Include When Reporting a Study Developing or Validating a Multivariable Prediction Model for Diagnosis or Prognosis			
Section/Topic	**Item**	**Development or Validation?**	**Checklist item**
Title and abstract			
Title	1	D;V	Identify the study as developing and/or validating a multivariable prediction model, the target population, and the outcome to be predicted.
Abstract	2	D;V	Provide a summary of objectives, study design, setting, participants, sample size, predictors, outcome, statistical analysis, results, and conclusions
Introduction			
Background and Objectives	3a	D;V	Explain the medical context (including whether diagnostic or prognostic) and rationale for developing or validating the multivariable prediction model, including references to existing models.
	3b	D;V	Specify the objectives, including whether the study describes the development or validation of the model, or both.
Methods			
Sources of Data	4a	D;V	Describe the study design or source of data (e.g., randomized trial, cohort, or registry data), separately for the development and validation datasets, if applicable.
	4b	D;V	Specify the key study dates, including start of accrual; end of accrual; and, if applicable, end of follow-up.
	4c	***D;V***	***Specifiy the type of data source (e.g. Electronic Medical Record, Health Information Exchange, Administrative Claims), the form (electronic vs. non), availability of data (e.g. open-source vs proprietary) and any efforts in data integration across sources (e.g. ontological alignment, entity***

			resolution).
Participants	5a	D;V	Specify key elements of the study setting (e.g., primary care, secondary care, general population) including number and location of centers.
	5b	D;V	Describe eligibility criteria for participants.
	5d	***D;V***	***Specify any key community characteristics (e.g. accessibility of health care resources, social support structure) relevant to an individual's ability to access care and support post-discharge.***
	5c	D;V	Give details of treatments received, if relevant.
Outcome	6a	D;V	Clearly define the outcome that is predicted by the prediction model, including how and when assessed.
	6b	D;V	Report any actions to blind assessment of the outcome to be predicted.
	6c	***D;V***	***Specify if all-cause readmissions were measured, or if readmissions were filtered by any of the following: 1. specific causes; 2. admits that were deemed unplanned; 3. admits that were unavoidable; 4. any other inclusion / exclusion criteria for the readmission event.***
Predictors	7a	D;V	Clearly define all predictors used in developing the multivariable prediction model, including how and when they were measured.
	7b	D;V	Report any actions to blind assessment of predictors for the outcome and other predictors.
Sample Size	8	D;V	Explain how the study size was arrived at.
Missing Data	9	D;V	Describe how missing data were handled (e.g., complete-case analysis, single imputation, multiple imputation) with details of any imputation method.
Statistical Analysis Methods	10a	D	Describe how predictors were handled in the analyses
	10b	D	Specify type of model (***including reasons for choosing specific models***), all model-building procedures (including ***detailed description of any algorithms used for feature selection***), and method for internal validation.
	10c	V	For validation, describe how the predictions were calculated.
	10d	D;V	Specify all measures used to assess model performance and, if relevant, to compare multiple models.
	10e	V	Describe any model updating (e.g., recalibration) arising from the validation, if done.
Risk Groups	11	D;V	Provide details on how risk groups were created, if

			done.
Development and Validation	12	V	For validation, identify any differences from the development data in setting, eligibility criteria, outcome, and predictors.
Results			
Participants	13a	D;V	Describe the flow of participants through the study, including the number of participants with and without the outcome and, if applicable, a summary of the follow-up time. A diagram may be helpful.
	13b	D;V	Describe the characteristics of the participants (basic demographics, clinical features, available predictors), including the number of participants with missing data for predictors and outcome.
	13c	V	For validation, show a comparison with the development data of the distribution of important variables (demographics, predictors, and outcome).
Model Development	14a	D	Specify the number of participants and outcome events in each analysis.
	14b	D	If done, report the unadjusted association between each candidate predictor and outcome.
Model Specification	15a	D	Present the full prediction model to allow predictions for individuals (i.e., all regression coefficients, and model intercept or baseline survival at a given time point).
	15b	D	Explain how to use the prediction model.
Model Performance	16a	D;V	Report performance measures (with CIs) for the prediction model.
	16b	***D;V***	***If possible, compare model performance statistically to other reference models used (e.g. CMS model) using the same cohort. When not possible, give a detailed comparison of model performance against previously published models with similar settings / cohorts.***
Model Updating	17	V	If done, report the results from any model updating (i.e., model specification, model performance).
Discussion			
Limitations	18	D;V	Discuss any limitations of the study (such as nonrepresentative sample, few events per predictor, missing data).
Implementation Efforts	***19***	***D;V***	***Discuss any model implementation efforts in detail, with discussion of implementation setting, successes, failures, and lessons learned. Of particular importance is any systematic approach to evaluating and comparing model effectiveness to previous workflows and / or alternative***

			readmission reduction efforts.
Interpretation	20a	V	For validation, discuss the results with reference to performance in the development data, and any other validation data.
	20b	D;V	Give an overall interpretation of the results, considering objectives, limitations, results from similar studies, and other relevant evidence.
Implications	21	D;V	Discuss the potential clinical use of the model and implications for future research.
Other Information			
Supplementary Information	22	D;V	Provide information about the availability of supplementary resources, such as study protocol, Web calculator, and datasets.
Technologies	***23***	***D;V***	***Report any specific technologies used, including but not limited to technologies for data storage/extraction/analysis and technologies used for patient education / communication during admission and post-discharge.***
Funding	24	D;V	Give the source of funding and the role of the funders for the present study.

Limitations to this study include the inability to include unpublished and proprietary commercial readmission prediction efforts. It is possible that health systems have attempted to develop their own readmission prediction models as part of internal initiatives. Further, commercial entities may have analytic modules for readmission analysis / prediction but fail to disclose models due to competitive advantages gained. Another limitation to this study was the possibility that search terms used were too specific, leading to a failure to capture relevant articles in the results. Future work should possibly reduce the search-term specificity and include other search engines. This study improves upon other similar efforts by gathering information that could be useful in assessing model generalizability (e.g. data source combinations) and proposing a framework for future reporting of 30-day readmission prediction efforts.

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Appendix

Table A1

Readmission risk prediction studies, including data sources and modes, cohort combinations used, model input variable categories, models used, model evaluation and important variables noted.

Cit	Data Source Combination & Mode	Cohort Combination	Input Variable Combination	Model Combination	Model Evaluation	Important Variables Noted
17	Medical Record (Electronic)	One Condition	Demographics, Diagnostic, Indexes, Social, Behavioral/Cognitive, Resource utilization	Bivariate analyses, Multivariate logistic regression	C-statistic (0.72) Derivation (mean = 0.73, CI: 0.71-0.75), Validation (mean = 0.69, CI: 0.63-0.74)	Tabak mortality score, Number of home address changes, Medicare member, Number of prior inpatient admissions. Slightly less significant were history of cocaine use, Single status, Male, and Anxiety and Depression.
18	Medical Record (Electronic)	One Condition	Diagnostic	Multivariate logistic regression	Model including rapid heart beat, swollen abdomen/feet and missed medications (C=0.21, sensitivity=0.5, specificity=0.81)	Rapid heart beat, Swollen abdomen

19	Medical Record (Electronic), Administrative (Electronic)	Group of conditions	Demographics, Diagnostic, Laboratory, Indexes, Social, Medications, LOS, Resource utilization	Bivariate analyses, Multivariate logistic regression	Derivation (C=0.64-0.73), Random sample validation (C=0.63-0.76), Historical validation (C=0.61-0.68)	LOS, Past admission within 30 days, Social history, Number of discharge meds, Steroids taken upon discharge, Hemoglobin count, Charlson index, Co-morbidities (Weight loss, Lymphoma, Hypertension, Degenerative neurologic disease, Solid tumor)
20	Administrative (Not available), Survey	All-Cause	Demographics, Indexes, Social, Resource utilization	Multivariate logistic regression	Derivation (C= 0.6468), Validation (C=0.6156)	Insurance type, Marital status, Possession of regular physician, Charlson Index, SF-12 Physical index, LOS > 2, # admissions in previous year
21	Administrative (Electronic)	All-Cause, One Condition	Demographics, Diagnostic, Procedure, Social, LOS, Resource utilization	Bivariate analyses, Multivariate logistic regression	All-cause (Training (C=0.75,0.79), Cross-site validation (C=0.78,0.81)), Pancreatitis (Training (C=0.71,0.65), Cross-site validation (C=0.65,0.73))	For All-cause: Admissions past 5 years, CPT codes including blood transfusion, Hydromorphone inj. , Tacrolimus (oral med), Bacterial culture, and Therapeutic or diagnostic injection. CP Model: Admissions past 5 years, ICM-9 CM code of radical pancreaticoduodenectomy, and 3 CPT Codes

22	Medical Record (Not available), Administrative (Not available)	All-Cause	Demographics, Diagnostic, Procedure, Laboratory, Social, Medications, LOS, Resource utilization, Other(Type and source of admission)	Bivariate analyses, Multivariate logistic regression, Other (SQLApe Algorithm (Striving for Quality Level and Analyzing of Patient Expenses) used to exclude unavoidable readmissions)	Derivation (C=0.69), Validation (C=0.71)	Low hemoglobin, Discharge from oncology, Low sodium, Procedure during stay, LOS > 5, Non-elective admission, Number of admissions prior year
23	Medical Record (Electronic)	Other	Demographics, Diagnostic, Indexes, Social, Medications, History, LOS, Discharge Location, Resource utilization	Bivariate analyses, Multivariate logistic regression	C=0.6	Age, Aminoglycoside use, Prior hospitalizations, Drug-resistant organism
24	Medical Record (Both Electronic and Non-electronic)	One Condition, Surgery	Demographics, Diagnostic, Procedure, Indexes, History	Bivariate analyses, Multivariate logistic regression	P <= 0.001	HCT co-morbidity index, Prep regimen (containing total body irradiation), Index admission infection
25	Administrative (Electronic)	All-Cause, Age-restricted	Demographics, Indexes, Social, Discharge Location, Resource utilization	Bivariate analyses, Multivariate logistic regression	P < 0.05, Elixhauser (Derivation (C=0.65), Validation (C=0.65)), HRDES models (Derivation C=0.63), Validation (C=0.63))	Age, Gender, Race, Discharge location, Insurance type, Surgery service, Major organ systems or systemic comorbid conditions, Distance to hospital (further away less likely to be readmitted)

26	Medical Record (Electronic)	Surgery	Demographics, Diagnostic, Procedure	Bivariate analyses, Multivariate logistic regression	P < 0.05, C=0.701	Female, Diabetes, Preoperative atrial fibrillation, COPD, Renal dysfunction, Distance category to hospital
27	Medical Record (Electronic)	Other	Demographics, Diagnostic, Procedure, History, LOS, Discharge Location, Resource utilization	Bivariate analyses, Multivariate logistic regression	P < 0.05, C=0.85	Presence of complication, Neck breather status, Discharge location, Illicit drug use, Severe coronary artery disease or Chronic lung disease
28	Medical Record (Not available), Administrative (Not available), Other (Not available - Census, National Death Index)	One Condition	Demographics, Laboratory, Indexes, Social, Vitals, Medications, History, Other(Discharge season (winter v. other seasons))	Bivariate analyses, Multivariate logistic regression	Clinical and nonclinical factors (C=0.69)	Living alone, HF Classification and Blood urea nitrogen were biggest factors. Less significant factors include Heart rate, Serum albumin, Discharge season, Presence of life-threatening arrhythmia, Diuretic use
29	Medical Record (Not available), Survey	All-Cause, Age-restricted	Demographics, Diagnostic, Indexes, Social, LOS, Other(Functional (ADL))	Other (ROC analyses for different index paritions for each of the three screening tools)	ISAR (C=0.442-0.505), TRST (C= 0.444-0.515), VIP (C=0.508-0.516)	None

30	Medical Record (Electronic), Administrative (Electronic)	All-Cause, One Condition, Other	Demographics, Diagnostic, Laboratory, Social, Discharge Location, Behavioral/Cognitive, Resource utilization, Other(Term-frequency-inverse document frequency from clinical notes)	Multivariate logistic regression, Other (Support Vector Machine)	All-cause (C=0.68), General symptoms readmission dx (C=0.71), CHF readmission dx (C=0.92), Procedure complications (C=0.88), Mood disorder (C=0.84), SVM (C=0.74)	Laboratory results, Visit history, Demographics, Prior ICD codes, Clinical keywords
31	Medical Record (Electronic), Administrative (Not available)	One Condition, Age-restricted	Demographics, Diagnostic, Laboratory, Vitals, History	Bivariate analyses, Multivariate logistic regression	P<0.001 for bi-variate, All-age model (C=0.61), Greater-than 65 y.o. model (C=0.59)	Age (lower), HCT (lower), BUN (higher), History of HF, History of COPD, History of Aortic Stenosis, History of stroke and Lower heart rate (for > 65 yo)

32	Medical Record (Electronic)	All-Cause	Demographics, Diagnostic, Procedure, Laboratory, Social, Vitals, Medications, History , LOS, Discharge Location, Resource utilization	Multivariate logistic regression	Admission Model (Derivation (C= 0.76), Validation internal (C=0.75), External validation without recalibaration (C=0.69), external validation with recalibration (C= 0.76)), Discharge Model (Derivation (C=0.78), Validation internal (C=0.77), External validation without recalibaration (C=0.71), External validation with recalibration (C=0.78))	Model improvement with addition of LOS, Conditions, Procedures and Discharge disposition
33	Administrative (Not available)	All-Cause, Other	Demographics, Diagnostic, Procedure, Indexes, Social, Discharge Location	Multivariate logistic regression	$P < 0.05$	Readmission Risk classification, Disability status, Number of surgeries, Bed section (intermediate location)
34	Medical Record (Not Electronic)	Group of conditions	Demographics, Diagnostic, Indexes, Resource utilization, Other(Episodes of seclusion or restraint)	Bivariate analyses, Multivariate logistic regression	$P < 0.05$, $P < 0.001$ for model fit	Number of previous admissions, BPRS scores for self-neglect and Thought disorder

35	Medical Record (Electronic), Administrative (Electronic)	All-Cause	Demographics, Diagnostic, Indexes, Social, Medications, LOS, Discharge Location, Resource utilization, Other(Activities of daily living, functional status, discharge season)	Bivariate analyses, Multivariate logistic regression	LACE alone, Cut-off 10 (C=0.711), LACE alone, Cut-off 8 (C=0.774), LACE with other factors (C=0.774)	LACE, Functional status, Insurance type, Possession of Primary Care Physician, ER admission (lower), Activities of daily living
36	Medical Record (Electronic), Administrative (Electronic)	All-Cause, Age-restricted	Demographics, Diagnostic, Social, History, Resource utilization	Multivariate logistic regression	P < 0.001, Derivation (C=0.819), Validation (0.824)	Age, Gender, Number of prior readmisions, Number of patient days (acute and non-acute), Number of diagnostic groups, Type of admission (emergent highest), Co-morbidities (renal dialysis highest)
37	Medical Record (Electronic), Administrative (Electronic), Other (Electronic - VA Office of Quality and Performance Stroke Special Project)	One Condition, Other	Demographics, Diagnostic, Indexes, Social, Vitals, Behavioral/Cognitive, Resource utilization, Other(Functional status)	Bivariate analyses, Multivariate logistic regression, Other (Net reclassification improvement for comparing social / clinical models over the CMS standard model)	CMS (C=0.636), CMS + Social (C=0.646), CMS + Social + Clinical (C=0.661)	Age, Number of co-morbidities, Metastatic cancer or Skin ulcers (Model 1), Low-income (Model 2), Age, Apache score, Skin ulcers (Model 3)

38	Medical Record (Electronic), Administrative (Electronic)	Age-restricted, Other	Demographics, Indexes, Social, Medications, Resource utilization, Hospital Characteristics, Other(Fragility-related diagnoses)	Bivariate analyses, Multivariate logistic regression	P < 0.001, C=0.6554	Co-morbidities (including presence of Mental illness (protective), Charlson index, and Fraility-related diagnoses), Previous hospitalization, Previous high-risk medication exposure, and Poverty level
39	Medical Record (Electronic), Administrative (Electronic), Other (Electronic - Chronic disease registry)	All-Cause	Demographics, Diagnostic, Laboratory, Indexes, Social, Vitals, Medications, Behavioral/Cognitive, Resource utilization, Other(Disability status, imaging report)	Bivariate analyses, Multivariate logistic regression, Other (CART (classification and regression trees), C5. 0 and Chi-square Automatic Interaction Detection (CHAID), and neural networks models)	P < 0.001 for bi-variate and logistic, Derivation (C=0.7), Validation (C=0.69)	Chronic conditions (CHF, COPD, Chronic Renal Failure, Arrythmia, Malignancy), Number of hospitalizations in previous year
40	Medical Record (Electronic), Other (Electronic - Humedica CDR)	One Condition	Demographics, Diagnostic, Procedure, Laboratory, Indexes, Medications, LOS, Discharge Location, Resource utilization	Bivariate analyses, Multivariate logistic regression	C=0.693	Diabetes treatment escalation, LOS, Previous hospitalizations w/in 6 mo, Payer type, Charlson Index, Co-morbidities (Hypertension and Heart failure)

41	Administrative (Electronic)	All-Cause, Other	Demographics, Diagnostic, Social, LOS	Multivariate logistic regression, Other (Complex custom model including elements of Hazards, Bayesian and Markov Chain Monte Carlo models, Other models used for comparison included classification and regression trees, a boosting algorithm (AdaBoost) and Bayesian networks)	MSE = 0.05 (Custom model), MSE = 0.16 (CART, boosting, logistic), MSE= 0.225 (Bayes Net)	Not available
42	Medical Record (Not available), Administrative (Electronic), Survey	All-Cause	Indexes, Resource utilization	Multivariate logistic regression	Derivation using LACE (C=0.7114), Validation (C=0.6935), External validation (C=0.684)	LOS, Acute emergent admission, Co-morbidity (Charlson Index), Visits to ER during prev. 6 mo.
43	Medical Record (Electronic)	All-Cause	Demographics, Diagnostic, Laboratory, Indexes, Social, Vitals, LOS, Resource utilization	Bivariate analyses, Multivariate logistic regression, Other (Integrated Discrimination Improvement for comparing models, and net reclassificatio n improvement)	24-hour model (C=0.69), 24-hour + Discharge model (C=0.71), Combined model significantly better discrimination than LACE and CMS model (NRI index, P < 0.001, IDI Index P < 0.05)	Several lab values (Albumin, HCT, Bun), Insurance type, Age, Past utilization, Elective admission
44	Administrative (Electronic)	All-Cause	Indexes, Resource utilization	Bivariate analyses	Not available	High LACE (>= 10) had RR of 2. 08

45	Medical Record (Electronic)	All-Cause	Demographics, Diagnostic, Procedure, Indexes, Discharge Location, Resource utilization, Other(Admission urgency)	Multivariate logistic regression	Non-clinical model (C=0.67), Charlson Index Model (C=0.69), SQLape-based model (C=0.72)	Charlson score, Previous admission, "High risk" operation or Malignancy under the SQLape categorization
46	Medical Record (Electronic), Administrative (Electronic)	One Condition, Age-restricted	Demographics, Diagnostic, Laboratory	Multivariate logistic regression	Administrative model (Derivation (C=0.60), Validation C=(0.60,0.61)), Medical record model (Derivation (C=0.58), Validation (C=0.61))	Administrative model (Acute coronary syndrome, renal failure, COPD, metastatic cancer or acute leukemia, severe hematologic disorders), Medical record model (Congestive heart failure, high BUN or creatinine, low hematocrit, history of heart disease)
47	Medical Record (Electronic), Administrative (Electronic)	All-Cause, Other	Demographics, Diagnostic	Multivariate logistic regression	P < 0.05 for individual variables, Charlson Index diagnoses model (C=0.675), Chronic Disease Score diagnoses model (C=0.68)	Charson Index diagnoses model (COPD, Diabetes, Metastatic solid tumor), Chronic Disease Score diagnoses model (Malignancies, Parkinson's Disease, Cardiac disease, Diabetes)
48	Administrative (Electronic), Other (Electronic - Quebec Trauma Registry)	Other	Demographics, Diagnostic, Indexes, Resource utilization, Other(Body region and mechanism of injury)	Multivariate logistic regression	P < 0.001, C=0.651	Age, Female, Injury Severity, Body region (Abdomen and Thorax), Number of prior admissions, Co-morbidities (Cancer and Pyschosis)

49	Administrative (Electronic)	Age-restricted, Group of conditions	Demographics, Diagnostic, Procedure, LOS	Multivariate logistic regression	P < 0.01, Condition-specific models ranged from C=0.56 (Respiratory failure, COPD, Angioplasty), C=0.62 (Prostatectomy), C=0.68 (Cholecystitis)	Cholecystitis (Gall bladder dysfunction / Carcinoma with operation, LOS, Non-operative gall bladder cases, Presence of cardiac disease), Prostatectomy (Benign prostatic hyperplasia, prostatic abcess, LOS)
50	Other (Electronic)	Surgery	Demographics, Diagnostic, Procedure, Laboratory, Indexes, Vitals, Other(Functional status)	Bivariate analyses, Multivariate logistic regression	P<0.05 for bivariate, Full model for ovarian (C=0.85), Full model for benign gynecologic disease (C=0.83)	ASA class, Functional status, Pre-operative conditions (including Diabetes and CHF), and Post-operative conditions (SSI, reoperation, Pulmonary embolism, UTI, Sepsis, Myocardial infarction)
51	Administrative (Electronic), Other (Electronic - Heart Failure registry (GWTG-HF) data)	One Condition, Age-restricted	Demographics, Diagnostic, Procedure, Laboratory, Vitals, History	Bivariate analyses, Multivariate logistic regression	Claims only model (C=0.587), Claims-clinical model (C=0.599)	Hemoglobin, Serum creatinine, Serum sodium, Systolic blood pressure
52	Administrative (Electronic), Other (Electronic - Registry - CSRS Cardiac Reporting System)	Surgery	Demographics, Diagnostic, Procedure, History, LOS, Hospital Characteristics	Bivariate analyses, Multivariate logistic regression	Readmission after CABG surgery (C=0.62)	Age, Gender, Body surface area, CHF, Postsurgical LOS, Co-morbidities (including Diabates, COPD, Hepatic failure), Dialysis, Annual surgeon volume, Discharge location, Hospital risk-

						adjusted mortality rate
53	Other (Electronic - National Surgical Quality Improvement Program database)	Surgery	Demographics, Diagnostic, Procedure, Laboratory, Indexes, Vitals, Medications, History, LOS, Discharge Location, Other(Functional status)	Bivariate analyses, Multivariate logistic regression	Derivation (C=0.681), Validation (C=0.646), Using Risk Score (C=0.676)	Thyroid malignancy, ASA > 2, Renal insufficiency, Hypoalbumine mia, Duration of stay > 1 day
54	Administrative (Electronic), Other (Electronic - Heart Failure registry (GWTG-HF) data)	One Condition, Age-restricted	Demographics, Diagnostic, Laboratory, Vitals, History, Resource utilization, Hospital Characteristics	Multivariate logistic regression	P < 0.05, Both models Derivation (C=0.59), Validation (C=0.59)	Hemoglobin, Discharge labs (Sodium, Creatinine), Age, Race, BNP, Toponin abnormal, BUN, Heart rate, Systolic BP at admission

Inclusion / Exclusion Criteria

IEC - 1: 30-Day Readmission

IEC - 2: Not a systematic review, meta-analysis, or editorial

IEC - 3: Not limited to a pediatric population (< 18 years old)

IEC - 4: Existence of a Prediction Model

References

[1] "Readmissions Reduction Program (HRRP)," 2016.

[2] L. Horwitz, C. Partovian, Z. Lin, J. Herrin, J. Grady, M. Conover, J. Montague, C. Dillaway, K. Bartczak, J. Ross, S. Bernheim, E. Drye and H. M. Krumholz, "Hospital-Wide (All-Condition) 30-Day Risk-Standardized Readmission Measure," Yale New Haven Health Services Corporation/Center for Outcomes Research & Evaluation, New Haven, Connecticut, 2011.

[3] "2014 Measure Updates and Specifications Report," Yale New Haven Health Services Corporation/Center for Outcomes Research & Evaluation, New Haven, Connecticut, 2014.

[4] M. V. Williams, "A requirement to reduce readmissions: take care of the patient, not just the disease," vol. 309, no. 4, pp. 394-396, 2013.

[5] K. E. Joynt and A. K. Jha, "Thirty-day readmissions--truth and consequences," vol. 366, no. 15, pp. 1366-1369, 2012.

[6] S. F. Jencks, M. V. Williams and E. A. Coleman, "Rehospitalizations among patients in the Medicare fee-for-service program," vol. 360, no. 14, pp. 1418-1428, 2009.

[7] A. Hines, M. Barrett, H. Jiang and C. Steiner, "Conditions With the Largest Number of Adult Hospital Readmissions by Payer, 2011," Agency for Healthcare Research and Quality, Rockville, MD, 2014.

[8] M. Barrett, L. Wier, H. Jiang and C. Steiner, "All-Cause Readmissions by Payer and Age, 2009-2013.," Agency for Healthcare Research and Quality, Rockville, MD, 2015.

[9] C. Boccuti and G. Casillas, "Aiming for Fewer Hospital U-turns: The Medicare Hospital Readmission Reduction Program," The Henry J. Kaiser Family Foundation, 2015.

[10] R. A. Berenson, R. A. Paulus and N. S. Kalman, "Medicare's readmissions-reduction program--a positive alternative," vol. 366, no. 15, pp. 1364-1366, 2012.

[11] F. PB and M. RA, "Revisiting hospital readmissions," vol. 309, no. 4, pp. 398-400, 2013.

[12] C. van Walraven, A. Jennings, M. Taljaard, I. Dhalla, S. English, S. Mulpuru, S. Blecker and A. J. Forster, "Incidence of potentially avoidable urgent readmissions and their relation to all-cause urgent readmissions," vol. 183, no. 14, pp. E1067--E1072, 2011.

[13] "Insights for Improvement, Reducing Readmissions: Measuring Health Plan Performance," 2012.

[14] D. Charles, M. Gabriel and T. Searcy, "Adoption of Electronic Health Record Systems among U.S. Non-Federal Acute Care Hospitals: 2008-2014," Office of the National Coordinator for Health Information Technology, Washington, DC, 2015.

[15] "Reducing Readmissions - Top Ways Information Technology Can Help," 2012.

[16] D. Kansagara, H. Englander, A. Salanitro, D. Kagen, C. Theobald, M. Freeman and S. Kripalani, "Risk prediction models for hospital readmission: a systematic review," vol. 306, no. 15, pp. 1688-1698, 2011.

[17] R. Amarasingham, B. J. Moore, Y. P. Tabak, M. H. Drazner, C. A. Clark, S. Zhang, W. G. Reed, T. S. Swanson, Y. Ma and E. A. Halm, "An automated model to identify heart failure patients at risk for 30-day readmission or death using electronic medical record data," *Medical care,* vol. 48, no. 11, pp. 981-988, 2010.

[18] A. H. Zai, J. G. Ronquillo, R. Nieves, H. C. Chueh, J. C. Kvedar and K. Jethwani, "Assessing hospital readmission risk factors in heart failure patients enrolled in a telemonitoring program," *International journal of telemedicine and applications,* vol. 2013, p. 1, 2013.

[19] C. Hebert, C. Shivade, R. Foraker, J. Wasserman, C. Roth, H. Mekhjian, S. Lemeshow and P. Embi, "Diagnosis-specific readmission risk prediction using electronic health data: a retrospective cohort study," *BMC medical informatics and decision making,* vol. 14, no. 1, p. 1, 2014.

[20] O. Hasan, D. O. Meltzer, S. A. Shaykevich, C. M. Bell, P. J. Kaboli, A. D. Auerbach, T. B. Wetterneck, V. M. Arora, J. Zhang and J. L. Schnipper, "Hospital readmission in general medicine patients: a prediction model," *Journal of general internal medicine,* vol. 25, no. 3, pp. 211-219, 2010.

[21] D. He, S. C. Mathews, A. N. Kalloo and S. Hutfless, "Mining high-dimensional administrative claims data to predict early hospital readmissions," *Journal of the American Medical Informatics Association,* vol. 21, no. 2, pp. 272-279, 2014.

[22] J. Donzé, D. Aujesky, D. Williams and J. L. Schnipper, "Potentially avoidable 30-day hospital readmissions in medical patients: derivation and validation of a prediction model," *JAMA internal medicine,* vol. 173, no. 8, pp. 632-638, 2013.

[23] G. M. Allison, E. G. Muldoon, D. M. Kent, J. K. Paulus, R. Ruthazer, A. Ren and D. R. Snydman, "Prediction model for 30-day hospital readmissions among patients discharged receiving outpatient parenteral antibiotic therapy," *Clinical infectious diseases,* vol. 58, no. 6, pp. 812-819, 2014.

[24] N. Bejanyan, B. J. Bolwell, A. Lazaryan, L. Rybicki, S. Tench, H. Duong, S. Andresen, R. Sobecks, R. Dean, B. Pohlman and others, "Risk factors for 30-day hospital readmission following myeloablative allogeneic hematopoietic cell transplantation (allo-HCT)," *Biology of Blood and Marrow Transplantation,* vol. 18, no. 6, pp. 874-880, 2012.

[25] M. D. Silverstein, H. Qin, S. Q. Mercer, J. Fong and Z. Haydar, "Risk factors for 30-day hospital readmission in patients? 65 years of age," in *Baylor {University} {Medical} {Center}. {Proceedings}*, 2008.

[26] V. A. Ferraris, S. P. Ferraris, R. C. Harmon and B. D. Evans, "Risk factors for early hospital readmission after cardiac operations," *The Journal of thoracic and cardiovascular surgery,* vol. 122, no. 2, pp. 278-286, 2001.

[27] E. M. Graboyes, T.-N. Liou, D. Kallogjeri, B. Nussenbaum and J. A. Diaz, "Risk factors for unplanned hospital readmission in otolaryngology patients," *Otolaryngology–Head and Neck Surgery,* vol. 149, no. 4, pp. 562-571, 2013.

[28] Q. L. Huynh, M. Saito, C. L. Blizzard, M. Eskandari, B. Johnson, G. Adabi, J. Hawson, K. Negishi, T. H. Marwick, M. Investigators and others, "Roles of nonclinical and clinical data in prediction of 30-day rehospitalization or death among heart failure patients," *Journal of cardiac failure,* vol. 21, no. 5, pp. 374-381, 2015.

[29] T. Braes, P. Moons, P. Lipkens, W. Sterckx, M. Sabbe, J. Flamaing, S. Boonen and K. Milisen, "Screening for risk of unplanned readmission in older patients admitted to hospital: predictive accuracy of three instruments," *Aging clinical and experimental research,* vol. 22, no. 4, pp. 345-351, 2010.

[30] C. Walsh and G. Hripcsak, "The effects of data sources, cohort selection, and outcome definition on a predictive model of risk of thirty-day hospital readmissions," *Journal of biomedical informatics,* vol. 52, pp. 418-426, 2014.

[31] S. Sudhakar, W. Zhang, Y.-F. Kuo, M. Alghrouz, A. Barbajelata and G. Sharma, "Validation of the Readmission Risk Score in Heart Failure Patients at a Tertiary Hospital," *Journal of cardiac failure,* vol. 21, no. 11, pp. 885-891, 2015.

[32] S. A. Choudhry, J. Li, D. Davis, C. Erdmann, R. Sikka and B. Sutariya, "A public-private partnership develops and externally validates a 30-day hospital readmission risk prediction model," *Online journal of public health informatics,* vol. 5, no. 2, p. 219, 2013.

[33] J. Holloway, S. V. Medendorp and J. Bromberg, "Risk factors for early readmission among veterans.," *Health services research,* vol. 25, no. 1 Pt 2, p. 213, 1990.

[34] C. Swett, "Symptom severity and number of previous psychiatric admissions as predictors of readmission.," *Psychiatric Services,* 1995.

[35] L. Spiva, M. Hand, L. VanBrackle and F. McVay, "Validation of a Predictive Model to Identify Patients at High Risk for Hospital Readmission," *Journal for Healthcare Quality,* 2014.

[36] E. Tsui, S. Y. Au, C. P. Wong, A. Cheung and P. Lam, "Development of an automated model to predict the risk of elderly emergency medical admissions within a month following an index hospital visit: A Hong Kong Experience," *Health informatics journal,* vol. 21, no. 1, pp. 46-56, 2015.

[37] S. Keyhani, L. J. Myers, E. Cheng, P. Hebert, L. S. Williams and D. M. Bravata, "Effect of clinical and social risk factors on hospital profiling for stroke readmission: a cohort study," *Annals of internal medicine,* vol. 161, no. 11, pp. 775-784, 2014.

[38] J. A. Pugh, C.-P. Wang, S. E. Espinoza, P. H. Noël, M. Bollinger, M. Amuan, E. Finley and M. J. Pugh, "Influence of Frailty-Related Diagnoses, High-Risk Prescribing in Elderly Adults, and Primary Care Use on Readmissions in Fewer than 30 Days for Veterans Aged 65 and Older," *Journal of the American Geriatrics Society,* vol. 62, no. 2, pp. 291-298, 2014.

[39] E. Shadmi, N. Flaks-Manov, M. Hoshen, O. Goldman, H. Bitterman and R. D. Balicer, "Predicting 30-day readmissions with preadmission electronic health record data," *Medical care,* vol. 53, no. 3, pp. 283-289, 2015.

[40] E. Eby, C. Hardwick, M. Yu, S. Gelwicks, K. Deschamps, J. Xie and T. George, "Predictors of 30 day hospital readmission in patients with type 2 diabetes: a retrospective, case–control, database study," *Current medical research and opinion,* vol. 31, no. 1, pp. 107-114, 2015.

[41] J. E. Helm, A. Alaeddini, J. M. Stauffer, K. M. Bretthauer and T. A. Skolarus, "Reducing hospital readmissions by integrating empirical prediction with resource optimization," *Production and Operations Management,* 2015.

[42] C. van Walraven, I. A. Dhalla, C. Bell, E. Etchells, I. G. Stiell, K. Zarnke, P. C. Austin and A. J. Forster, "Derivation and validation of an index to predict early death or unplanned readmission after discharge from hospital to the community," *Canadian Medical Association Journal,* vol. 182, no. 6, pp. 551-557, 2010.

[43] R. Amarasingham, F. Velasco, B. Xie, C. Clark, Y. Ma, S. Zhang, D. Bhat, B. Lucena, M. Huesch and E. A. Halm, "Electronic medical record-based multicondition models to predict the risk of 30 day readmission or death among adult medicine patients: validation and comparison to existing models," *BMC medical informatics and decision making,* vol. 15, no. 1, p. 1, 2015.

[44] A. Gruneir, I. A. Dhalla, C. van Walraven, H. D. Fischer, X. Camacho and P. Rochon, "Unplanned readmissions after hospital discharge among patients identified as being at high risk for readmission using a validated predictive algorithm," *Open Medicine,* vol. 5, no. 2, pp. 104-111, 2011.

[45] P. Halfon, Y. Eggli, I. Prêtre-Rohrbach, D. Meylan, A. Marazzi and B. Burnand, "Validation of the potentially avoidable hospital readmission rate as a routine indicator of the quality of hospital care," *Medical care,* vol. 44, no. 11, pp. 972-981, 2006.

[46] P. S. Keenan, S.-L. T. Normand, Z. Lin, E. E. Drye, K. R. Bhat, J. S. Ross, J. D. Schuur, B. D. Stauffer, S. M. Bernheim, A. J. Epstein and others, "An administrative claims measure suitable for profiling hospital performance on the basis of 30-day all-cause readmission rates among patients with heart failure," *Circulation: Cardiovascular Quality and Outcomes,* vol. 1, no. 1, pp. 29-37, 2008.

[47] J. P. Parker, J. S. McCombs and E. A. Graddy, "Can pharmacy data improve prediction of hospital outcomes?: Comparisons with a diagnosis-based comorbidity measure," *Medical care,* vol. 41, no. 3, pp. 407-419, 2003.

[48] L. Moore, H. T. Stelfox, A. F. Turgeon, A. B. Nathens, A. Lavoie, G. Bourgeois and J. Lapointe, "Derivation and validation of a quality indicator for 30-day unplanned hospital readmission to evaluate trauma care," *Journal of Trauma and Acute Care Surgery,* vol. 76, no. 5, pp. 1310-1316, 2014.

[49] J. W. Thomas, "Does risk-adjusted readmission rate provide valid information on hospital quality?," *Inquiry,* pp. 258-270, 1996.

[50] K. Dessources, J. Y. Hou, A. I. Tergas, W. M. Burke, C. V. Ananth, E. Prendergast, L. Chen, A. I. Neugut, D. L. Hershman and J. D. Wright, "Factors associated with 30-day hospital readmission after hysterectomy," *Obstetrics \& Gynecology,* vol. 125, no. 2, pp. 461-470, 2015.

[51] B. G. Hammill, L. H. Curtis, G. C. Fonarow, P. A. Heidenreich, C. W. Yancy, E. D. Peterson and A. F. Hernandez, "Incremental value of clinical data beyond claims data in predicting 30-day outcomes after heart failure hospitalization," *Circulation: Cardiovascular Quality and Outcomes,* vol. 4, no. 1, pp. 60-67, 2011.

[52] E. L. Hannan, M. J. Racz, G. Walford, T. J. Ryan, O. W. Isom, E. Bennett and R. H. Jones, "Predictors of readmission for complications of coronary artery bypass graft surgery," *Jama,* vol. 290, no. 6, pp. 773-780, 2003.

[53] J. C. Iannuzzi, F. J. Fleming, K. N. Kelly, D. T. Ruan, J. R. Monson and J. Moalem, "Risk scoring can predict readmission after endocrine surgery," *Surgery,* vol. 156, no. 6, pp. 1432-1440,

2014.

[54] Z. J. Eapen, L. Liang, G. C. Fonarow, P. A. Heidenreich, L. H. Curtis, E. D. Peterson and A. F. Hernandez, "Validated, electronic health record deployable prediction models for assessing patient risk of 30-day rehospitalization and mortality in older heart failure patients," *JACC: Heart Failure,* vol. 1, no. 3, pp. 245-251, 2013.

[55] W. Yu, T. Liu, R. Valdez, M. Gwinn and M. J. Khoury, "Application of support vector machine modeling for prediction of common diseases: the case of diabetes and pre-diabetes," *BMC Medical Informatics and Decision Making,* vol. 10, no. 1, p. 16, 2010.

[56] S. Dreiseitl and L. Ohno-Machado, "Logistic regression and artificial neural network classification models: a methodology review," *Journal of Biomedical Informatics,* vol. 35, no. 5–6, pp. 352-359, #oct# 2002.

[57] F. Amato, A. López, E. M. Peña-Méndez, P. Vaňhara, A. Hampl and J. Havel, "Artificial neural networks in medical diagnosis," *Journal of Applied Biomedicine,* vol. 11, no. 2, pp. 47-58, 2013.

[58] K. G. Moons, J. A. de Groot, W. Bouwmeester, Y. Vergouwe, S. Mallett, D. G. Altman, J. B. Reitsma and G. S. Collins, "Critical appraisal and data extraction for systematic reviews of prediction modelling studies: the CHARMS checklist," *PLoS Med,* vol. 11, no. 10, p. e1001744, 2014.

[59] G. S. Collins, J. B. Reitsma, D. G. Altman and K. G. Moons, "Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD): the TRIPOD Statement," *BMC Medicine,* vol. 13, p. 1, 2015.

Curriculum Vitae

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EDUCATION

2004-2008 **Bachelor of Arts, Human Biology**

Brown University, Providence, RI

PROFESSIONAL AND RESEARCH EXPERIENCE

Oct. 2014 - Present *Research Scientist*

CUBRC, Inc. Information Exploitation Sector, Buffalo, NY

- Key part of a business initiative tasked to adopt and develop information technology for health informatics applications for insurance companies and providers
- Active development of a complex event processing application for detection and notification of medical non-adherence events in pharmacy claims data
- Active development of a distributed triple storage system for healthcare data and graph-based data exploration and analysis using basic formal ontology (BFO)-compliant medical ontologies

Jun. 2013-Oct. 2014 *Research Assistant*

Center for Population Health Information Technology, JH Bloomberg School of Public Health,

Dr. Hadi Kharrazi

- Extraction, parsing and normalization of HL7 v2 ADT messages from the Maryland Health Information Exchange for use in a readmissions risk prediction algorithm

Jan. 2012-July 2014 *Research Contractor*

Section on Integrative Neuroimaging, National Institutes of Mental Health, NIH, Bethesda, MD

Dr. Karen F. Berman

- Lead programmer, development of MSSQL database and Java GUI for research data collection

Jan. 2010-Jan. 2012 *Postbaccalaureate Intramural Research Training Award (IRTA) Fellowship*

- Lead Programmer, Computational neuroscience of dopamine mediation of incentive-

based decision-making measured by PET Fluro-DOPA receptor imaging in healthy adults
- Lead Analyst, Assessment of genotype effects (BDNF & COMT) on human decision-making behavior

Mar. 2009-Dec. 2009 *Research Support Specialist*

CUBRC, Buffalo, NY

- Designed and integrated statistical routines for web-based relational database for DoD clinical research of Traumatic Brain Injuries
- Interfaced MySQL, R, Java and Java Server Pages

May 2008-Feb. 2009 *Research Assistant*

Bioacoustics Research Program, Cornell Lab of Ornithology Dr. Sandra Vehrencamp

- Designed experimental analysis testing for singing patterns in aggressive songbird interactions
- Three months of fieldwork in a tropical dry forest in Costa Rica
- Organized, processed and analyzed acoustic and behavioral data using custom MATLAB scripting, leading to a peer-reviewed publication

Jun. 2007-May 2008 *Research Assistant*

Brown University Psychology Laboratory Dr. Andrea Megela Simmons, Dr. James Simmons

- Analysis of vocal interactions in natural bullfrog choruses using a novel microphone array system, leading to a peer-reviewed publication
- Processed and analyzed sound and location data using custom MATLAB routines

PEER-REVIEWED PUBLICATIONS

1. Bates ME, **Cropp BF**, Gonchar M, Knowles J, Simmons JA, Simmons AM. Spatial location influences vocal interactions in bullfrog choruses. *The Journal of the Acoustical Society of America* 127, no. 4 (April 2010): 2664-2677.

2. Goker-Alpan O, Masdeu JC, Kohn PD, Ianni A, Lopez G, Groden C, Chapman MC, **Cropp BF**, Eisenberg DP, Maniwang ED, Davis J, Wiggs E, Sidransky E, Berman KF. The neurobiology of glucocerebrosidase-associated parkinsonism: a positron emission tomography study of dopamine synthesis and regional cerebral blood flow. *Brain* (2012) 135(8): 2440-2448

3. Nguyen TV, McCracken JT, Ducharme S, **Cropp BF**, Botteron KN, Evans AC, Karama S. Interactive Effects of DHEA and Testosterone on Cortical Thickness during Early Brain Development" *Journal of Neuroscience* (2013) 33(26): 10840-10848

4. Jabbi M, Nash T, Kohn P, Ianni A, Coutlee C, Holroyd T, Carver F, Chen Q, **Cropp BF**, Kippenhan JS, Robinson S, Coppola R, Berman KF. Convergent BOLD and beta-band activity in superior temporal sulcus and frontolimbic circuitry underpins human emotion cognition. *Cerebral Cortex* (2014): bht427.

5. Vehrencamp SL, Ellis JM, **Cropp BF**, Koltz J. Negotiation of territory boundaries in the banded wren. *Behavioral Ecology* (2014).

6. Jabbi, M, Prabhakaran, R, Ekuta, V, Damme, K, **Cropp, B**, Roe, K, ... Berman, KF. Human Superior Temporal Sulcus Subserves both Concrete and Abstract Social Cognition in Typical Development. *Neuropsychopharmacology* (2014, December): (Vol. 39, pp. S502-S503).

CONFERENCE PROCEEDINGS

1. **Cropp BF**, Jabbi M, Kohn P, Nash T, Raila H, Kippenhan JS, Eisenberg D, Masdeu J, Berman KF. Midbrain dopamine modulates mesocorticolimbic and sensorimotor regulation of decision-making.

17th annual meeting, Organization for Human Brain Mapping (HBM). June 2011, Quebec City, Canada.

41nd annual meeting of the Society for Neuroscience (SFN). October 2011, Washington DC.

67th annual meeting, Society of Biological Psychiatry (SOBP). May 2012, Philadelphia, PA.

2. **Cropp BF**, Bates ME, Simmons JA, Simmons AM. Spatial and temporal organization of acoustic interactions in bullfrog choruses*. 12th Congress of the International Behavioral Ecology (ISBE)*.