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A literature review of preventable hospital readmissions: Preceding the Readmissions Reduction Act

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ABSTRACT

Preventable readmissions are a large and growing concern throughout healthcare in the United States, representing as many as 20% of all hospitalizations (30-day post-discharge) and an estimated $17 to $26 billion in unnecessary costs annually. National quality initiatives and Medicare reimbursement financial incentives have stimulated significant efforts by healthcare organizations to reduce readmissions via a number of approaches and interventions. Given the severity and complexity of this problem, this article explores the literature describing descriptive and predictive readmission studies as well as proposed interventions that used a systems engineering approach before the 2011 Medicare program to stimulate reduction of readmissions. A total of 112 publications from 1988 to 2011 were identified and grouped into three general categories: descriptive analyses, intervention studies, and predictive analyses. While a significant amount of work has been conducted in each of these areas, very few systems engineering, industrial engineering, and operations research studies have focused directly on the hospital readmission issue. This article, therefore, concludes with a discussion of potential areas in which industrial engineers could make meaningful contributions to this significant issue.

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1. Background

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

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

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

Estimates of the percent of discharged adult patients readmitted within a month of their original hospitalization range from 5% to 29% (Thomas and Holloway, 1991), with 90% of these readmissions estimated as unplanned (Jencks *et al.*, 2009). For Medicare fee-for-service beneficiaries discharged between July 2005 and June 2008, the median 30-day readmission rates were 19.9% for acute myocardial infarction (AMI) and 24.4%

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for heart failure (HF) (Krumholz *et al.*, 2009), with the overall annual cost of unplanned re-hospitalizations estimated at $17.4 billion in 2004 (Jencks *et al.*, 2009). According to hospital discharge data for residents of New York, Pennsylvania, Tennessee, and Wisconsin from January to July 1999, hospital costs for preventable readmissions were roughly $730 million (Friedman and Basu, 2004). Readmitted patients also tend to have significantly poorer outcomes and longer lengths of stay. More broadly, readmissions often are proposed as a general marker for the quality of care received during an index admission (Weissman *et al.*, 1999). For example, early unplanned readmissions of patients with heart failure, diabetes, and obstructive lung disease have been linked to the quality of care during their previous hospital stay (Ashton *et al.*, 1995).

Despite this evidence and ensuing efforts to reduce readmissions, Karen E. Joynt and A. K. Jha (2012) found that risk-adjusted 30-day readmission rates for congestive heart failure, pneumonia and acute myocardial infarction between 2002 and 2009 showed little improvement, arguing that overall 30-day readmission rates for these conditions may not appropriately reflect the quality of care because causes for most of those readmissions may not be under the hospital's control. The Dartmouth Atlas Project, in collaboration with the Goodman *et al.* (2013), reported that overall improvement in 30-day readmission rates between 2008 and 2010 has been "slow and inconsistent" throughout academic hospitals in the United States. The report points out that focusing on 30-day readmission rates may not improve the health of patients because it may lead to neglecting other important aspects of care, such as the prevention of longer-term readmissions for patients with chronic diseases and the increase in hospital mortality (Goodman *et al.*, 2013; Robert Wood Johnson Foundation, 2013). Still, 30-day readmission rates continue to be the metric used to evaluate the performance of hospitals.

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

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

2. Methods

The articles included in this literature review used systems engineering approaches to study the hospital readmission issue before the introduction of Medicare's new reimbursement policy. We included all articles published in peer-reviewed venues from 1988 to 2011 (new federal and state-level incentives to reduce hospital readmissions were introduced in mid-2011). An article was included in the data collection sample if it (1) used a systems approach to (2) describe the hospital readmission problem, (3) predict patient-level hospital readmission risk, and (4) present findings of interventions to reduce preventable hospital readmissions in (5) US healthcare institutions. An article was excluded from the sample if it (1) did not use a systems approach or (2) it presented findings of reducing hospital readmissions in countries other than the US. The information source was PubMED and the search key was "hospital readmission." Of the articles found, a total of 112 articles from 1988 through 2011 were included based on the predetermined inclusion/exclusion criteria. Two reviewers performed a blind screening of title and abstract against the eligibility criteria previously described. Any discrepancies regarding eligibility for particular articles were discussed between the two authors and resolved by consensus. Any uncertainty as to eligibility was referred to a third author. Full-text articles were assessed if eligibility could not be determined from title and abstract. Independently, five authors collected data from the final sample of articles using piloted forms. The data items used in our data collection strategy included: type of study (descriptive, predictive, intervention), patient population and study setting (age, disease, type of insurance, cohort size, and readmission time interval), readmission time interval (seven-day, 30-day, one-year readmission, etc.), intervention type (discharge process, transition of care, follow-up), and demographic and clinical factors associated with hospital readmission.

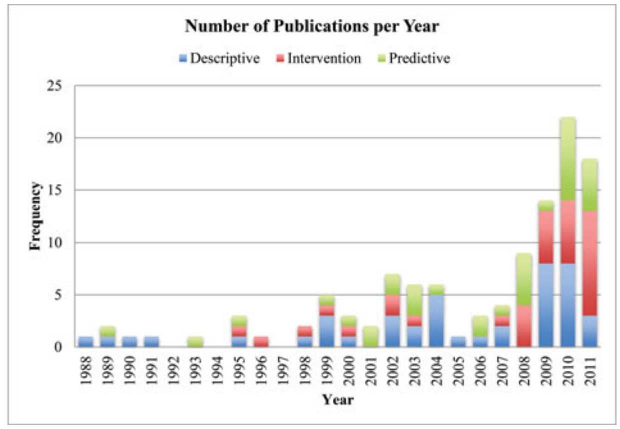

Figure 1. Publications categorized as descriptive, intervention, or predictive.

As summarized in Fig. 1, the number of papers in each category increased significantly in the past few years, somewhat coinciding with the 2009 announcement of Medicare's new reimbursement policy. Partly driven by these reporting and financial motivations, institutions and researchers have developed a variety of strategies to identify and reduce preventable readmissions. Some studies have focused on describing the readmissions landscape at the national level, while others have focused on the local and hospital levels. There have been a number of predictive studies exploring risk factors for different patient groups to better understand the dynamics of readmissions. These studies have shown a pervasive lack of standard systems or processes to ensure post-discharge compliance to exercise treatment instructions (e.g., medication, diet, and follow-up care) (Krumholz *et al.*, 2002), so a number of the studies have focused on developing interventions to improve information transfer and other aspects of the discharge process. We grouped

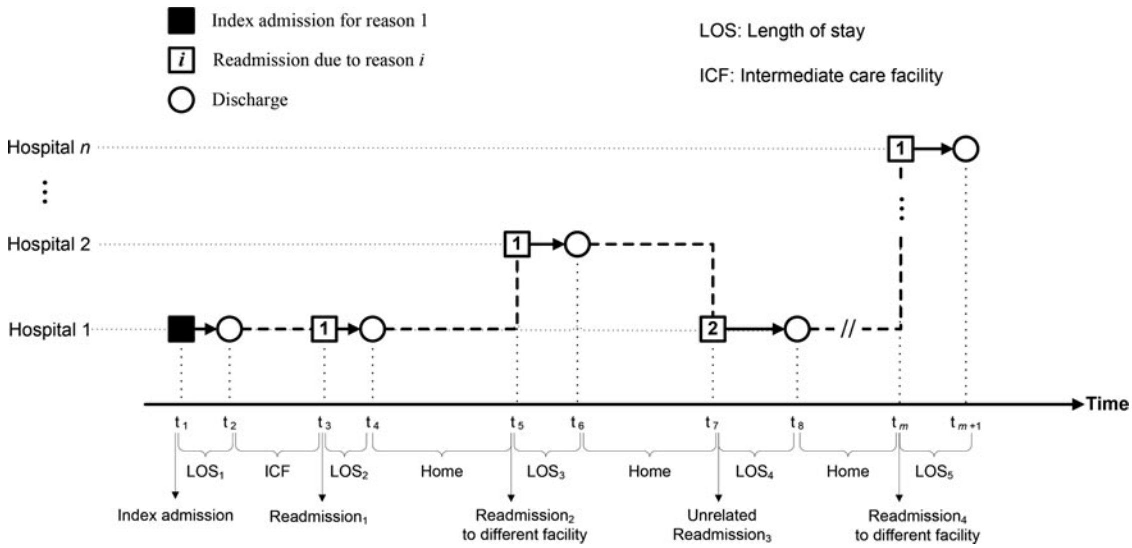

Figure 2. General readmissions context.

the papers into three categories: descriptive analysis (43), intervention studies (34), and statistical or predictive models (35).

The remainder of this article is organized as follows: Section 2 discusses definitions, measurements, and descriptive analyses reported in the literature; Section 3 summarizes common preventive approaches proposed, evaluated or practiced by healthcare institutions; Section 4 reviews statistical and predictive models discussed in the literature; and Section 5 discusses research gaps and opportunities for future work on reducing readmissions from an industrial engineering approach.

3. Results

3.1. Definitions, measurements, and descriptive analyses

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

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

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

Readmissions can also be classified as planned or unplanned, where planned refers to an intentional admission that is a scheduled part of a patient's care plan, such as chemotherapy or rehabilitation. One study estimated that 47.1% of patients readmitted within 30 days were unplanned (Maurer and Ballmer, 2004). Unplanned readmissions can be either (potentially) preventable (e.g., congestive heart failure, bacterial pneumonia, urinary tract infection, surgical wound infection) or non-preventable (e.g., trauma, unexpected finding of malignancy). While estimates vary for the percent of unplanned admissions that are preventable, Jiang, Russo, and Barrett (2009) report, in

Table 1. Proportion of preventable readmissions among unplanned readmissions.

Study	Group	Design[1]	Number patients	Time interval, day	Number of readmissions/rates	Preventable readmissions, % of all readmissions
Clarke (1990)	General medical and	R			(in total 100 random case notes)	31.5
	geriatric		207	0–6	(74 were available)	6.3 (Total: 16.5)
	Surgical		166	21–27	25 case notes (18 available)	49.3
			60	0–6	25 case notes (19 available)	19.0 (Total: 34.6)
			48	21–27	25 case notes (19 available)	
					25 case notes (18 available)	
Miles and Lowe (1999)	All RA data from JHH[2] in Oct. 1998 by ACHS[3] indicator	R	3081 admissions	28	437 readmissions with adequate data involving 371 patients	5.5 (out of the 437 readmissions)
Maurer and Ballmer (2004)	DIM[4] of KSW[5]	P	884 IA[6]	30	12.3%	9.4
				90	19.5% (planned and unplanned)	18.5 (out of unplanned)
Friedman and Basu (2004)	Persons with initial PQI[7] admission	R	345,651	3 mo	–	13.3%
				6 mo	35.3%	19.4% (out of the PQI admissions)

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

a study of nearly 4.4 million admissions in 2006, that 18% of the adult admissions were potentially preventable. Ascertaining whether a patient's condition is preventable or not can exacerbate the accurate identification of a readmission. In practice, making this determination is often assessed by various types of clinical experts (e.g. surgeons, general physicians) whose background may influence their analyses and conclusions.

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

3.2. Prevention interventions

Most of the intervention articles reviewed culled recommendations from the literature or experimental studies. Summaries of many of these interventions can be found in Greenwald *et al.*, (2007), Kanaan (2009), Olson *et al.* (2011), Simmons (2010) and Taylor (2010). Osei-Anto *et al.* (2010) and Jweinat (2010) summarize successful interventions and provide a framework for the development of readmission prevention programs in hospitals. Two of the papers—Trisolini *et al.* (2008) and HealthleadersMedia (2010)—focus on healthcare quality.

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

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

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

Common interventions directed towards post-discharge, follow-up care included the following: (1) increased frequency or intensity of follow-up activities (Rayner *et al.*, 2002; Rich *et al.*, 1995); (2) increased primary care access (Cline *et al.*, 1998; Strunin *et al.*, 2007; Weinberger *et al.*, 1996); (3) high-risk screening tools to determine the need for intervention (Manning, 2011); (4) home health monitoring technology (Institute for Healthcare Improvement, 2010a); (5) improved communication between primary care and inpatient providers to facilitate timely and accurate transfer of key patient information (Ornstein *et al.*, 2011); (6) healthcare worker (e.g., physician, nurse, physiotherapist) visits after discharge (Andersen *et al.*, 2000;

Table 2. Summary of common interventions discussed in the literature.

Intervention type	Intervention	References
Discharge planning	Disease and treatment education	(Balaban *et al.*, 2008; Bickmore *et al.*, 2009; Bisognano and Boutwell, 2009; Cline *et al.*, 1998; Institute for Healthcare Improvement, 2009a, 2009b, 2010a; Jack *et al.*, 2008; Manning, 2011; Naylor *et al.*, 1999; Ornstein *et al.*, 2011; Patient Safety Authority, 2005; Rich *et al.*, 1995; Weinberger *et al.*, 1996)
	Review of medication	(Bisognano and Boutwell, 2009; Cline *et al.*, 1998; Fleming and Haney, 2013; Institute for Healthcare Improvement, 2009a, 2010a; Kasper *et al.*, 2002; Osei-Anto *et al.*, 2010; Rich *et al.*, 1995; Weinberger *et al.*, 1996)
	Prescribed diet	(Rich *et al.*, 1995)
	Assignment of PCP	(Osei-Anto *et al.*, 2010; Weinberger *et al.*, 1996)
	Self-management education	(Cline *et al.*, 1998; Coleman *et al.*, 2006; Fleming and Haney, 2013; Institute for Healthcare Improvement, 2009a, 2010a; Jack *et al.*, 2008; Manning, 2011; Osei-Anto *et al.*, 2010; Patient Safety Authority, 2005)
	Identify sources of error/risk at discharge	(Anthony *et al.*, 2005; Institute for Healthcare Improvement, 2009b)
	Risk screen patients	(Institute for Healthcare Improvement, 2010b; Manning, 2011; Osei-Anto *et al.*, 2010)
	Interdisciplinary/multi-disciplinary clinical team	(Osei-Anto *et al.*, 2010)
Transitions of care	Computer-enabled discharge communication	(Motamedi *et al.*, 2011)
	Effective patient and family engagement	(Institute for Healthcare Improvement, 2010a, 2010b)
	Coordination among care sites	(Bisognano and Boutwell, 2009; Bodenheimer, 2008; Coleman *et al.*, 2006; Fleming and Haney, 2013; Institute for Healthcare Improvement, 2009a, 2009b, 2010a, 2010b; Jacobs, 2011; Manning, 2011; Motamedi *et al.*, 2011; Ornstein *et al.*, 2011; Osei-Anto *et al.*, 2010; Press *et al.*, 2010)
	Assignment of a care transitions coordinator/transitions coach	(Coleman *et al.*, 2006; Fleming and Haney, 2013)
Follow-up	Home visits	(Andersen *et al.*, 2000; Naylor *et al.*, 1999; Osei-Anto *et al.*, 2010; Rich *et al.*, 1995)
	Telephone contact	(Balaban *et al.*, 2008; Bisognano and Boutwell, 2009; Cline *et al.*, 1998; Harrison *et al.*, 2011; Institute for Healthcare Improvement, 2009a; Jacobs, 2011; Kasper *et al.*, 2002; Naylor *et al.*, 1999; Osei-Anto *et al.*, 2010; Rich *et al.*, 1995; Weinberger *et al.*, 1996)
	Compliance with instructions given at hospital	(Harrison *et al.*, 2011; Jacobs, 2011; Motamedi *et al.*, 2011; Rich *et al.*, 1995; Weinberger *et al.*, 1996)
	Primary care clinic follow-up appointment	(Coleman *et al.*, 2006; Grafft *et al.*, 2010; Institute for Healthcare Improvement, 2009b, 2010a; Jordan *et al.*, 2012; Kasper *et al.*, 2002; Osei-Anto *et al.*, 2010; Rayner *et al.*, 2002; Weinberger *et al.*, 1996)
	Access to nurse consultation (short notice)	(Cline *et al.*, 1998; Naylor *et al.*, 1999)
	Medical rehabilitation/therapy after discharge	(Jordan *et al.*, 2012; Mudrick *et al.*, 2013)

Ornstein *et al.*, 2011); and (7) phone-based follow-up after discharge (Harrison *et al.*, 2011; Kasper *et al.*, 2002) or a combination of visits and phone calls after discharge (Naylor *et al.*, 1999).

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

Even though most studies developed their proposed interventions based on widely accepted good clinical practices and patient-centered care, three studies did not find significant differences between intervention and control groups (Grafft *et al.*, 2010; Rayner *et al.*, 2002; Weinberger *et al.*, 1996). One

Table 3. Common diagnoses mentioned in the intervention literature.

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

study found that the efficacy of their intervention was relatively smaller in congestive heart failure patients as compared to other patients (Naylor *et al.*, 1999), which may suggest the need to tailor interventions according to the needs of different patient groups. A recent report from the Agency for Healthcare Research and Quality on the effectiveness of interventions to improve transitions for acute stroke and myocardial infarction patients found that, while some outcomes, such as hospital length of stay and mortality, are often improved by intervention, most studies have not been able to clearly demonstrate a positive or negative effect on metrics of systems' or patient's outcomes (Olson *et al.*, 2011).

Five studies included a cost analysis based on costs per patient, annual healthcare cost per patient, total Medicare reimbursements for health services at 24 weeks after discharge, discharge costs, and possible implications of readmission cost policies on care quality (Balaban *et al.*, 2008; Cline *et al.*, 1998; Naylor *et al.*, 1999; Rich *et al.*, 1995; Simmons, 2010). Cost-benefit analysis of interventions is especially important in light of the Medicare reimbursement penalty for those hospitals with consistently increased readmission rates.

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

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

3.3. Statistical and predictive analysis

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

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

Another important body of literature has to do with constructing statistical models to predict readmission rates. Table 5 summarizes papers from 1989 through 2010 related to readmission prediction, and Table 6 summarizes the focus of each paper and the frequency of the common predictive factors. Age and gender were the two most common predictive factors analyzed and have appeared in roughly two-thirds of all examined papers. Comorbidity, the patient length of stay, the number and nature of prior admissions, and ethnicity were also commonly identified as predictive factors. Other studies focused on very specific predictive factors, especially those that considered a subset of patients, with specific diagnoses or diseases sometimes tested as independent or causal variables. In a study of psychiatric patients, for instance, Hendryx *et al.* (2003) examined the association between a primary diagnosis of schizophrenia and subsequent readmission.

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

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

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

Table 4. Factors associated with readmissions.

Study	Factor	Sample Group, N = sample size	Results
Elixhauser *et al.* (1998)	Comorbidity	Non-maternal inpatients from 438 acute care hospitals California N = 1,779,167	Comorbidities were associated with longer length of stay, higher hospital charges, and mortality and had different effects among different patient groups
van Walraven *et al.* (2002)	Discharge summary availability	Patients discharged for acute medical illness from Ottawa Civic Hospital with OHIP[1] number N = 888	A decreased trend in readmissions was found when the factor was added (relative risk, 0.74)
Krumholz *et al.* (2002)	Education and support	Patients in YNHH[2] with heart failure from Oct. 1997 to Sep.1998, age≥ = 50 N = 88	Intervention group had a significantly lower risk of readmission (hazard ratio, 0.56)
Riegel *et al.* (2002)	Nurse case-management telephone intervention	Patients with heart failure from two southern California hospitals N = 358	The heart failure hospitalization rate was 45.7% and 47.8% lower in the intervention group at three and six months
Moore *et al.* (2003)	Medical errors related to discontinuity care from inpatient to outpatient setting	General patients who had been hospitalized at a large academic medical center N = 86	49% of patients experienced at least one medical error and patients with work-up error were 6.2 times more likely to be re-hospitalized within three months
Dormann *et al.* (2004)	Adverse drug reactions	General patients from internal medicine of UHEN[3]; N = 1000 admissions	ADRs were not significant with readmissions but with LOS
Lappe *et al.* (2004)	Hospital-based discharge medication program (DMP)	Cardiovascular disease from the 10 largest hospitals in UIHS[4]: Pre-DMP(1996–1998): N = 26000; DMP (1999–2002): N = 31465	Reduced relative risk for death and readmissions (hazard ratios, 0.81, 0.92)
Ather, Chung, Gregory, and Demissie (2004)	Insurance provider	Adults with asthma from NJDHHS[5]; N = 15864	Significant increased risk of seven-day readmission for managed care patients compared to indemnity (OR, 1.67) and LOS is also significant for readmissions
Koelling *et al.* (2005)	One-hour discharge education	Patients with chronic heart failure from University of Michigan Hospital; N = 223; Control group = 116	Patients receiving the education intervention had lower risk of re-hospitalization (relative risk, 0.65)
Vira, Colquhoun, and Etchells (2006)	Medication reconciliation	Generally from a Canadian community hospital; N = 60	18% of patients were detected having clinical important unintended variance after reconciliation
Kartha *et al.* (2007)	Depression	Adults inpatient with at least one hospital admissions in the past six month; N = 144	Depression tripled the odds of re-hospitalization (odds ratio, 3.3)
Bailey *et al.* (2009)	Risks of severity	Indigenous and non-indigenous children of bronchiolitis from Royal Darwin Hospital, age≤2; N = 101	No significant difference for readmission rates among the two groups, but indigenous children had more severe illness
Jha, Orav, and Epstein (2009)	Public reporting of discharge planning	Congestive heart failure, using HQA[6] database	No large reduction in unnecessary readmissions
Jack *et al.* (2009)	A reengineered hospital discharge program	Adults patients admitted to medical teaching service of Boston Medical Center; N = 749	The intervention group (N = 370) had a lower rate of hospital utilization (0.314 vs 0.451 visit per person per month)
Hernandez *et al.* (2010)	Early physician follow-up	Patients ≥65 with heart failure from 225 hospitals; N = 30316	Patients who are discharged from hospitals that have higher early follow-up rates have a lower risk of 30-day readmission
Boulding *et al.* (2011)	Patient satisfaction	430,982 patients with acute myocardial infarction (AMI) 1,029,578 patients with heart failure 912,522 patients with pneumonia	Higher overall satisfaction and satisfaction with discharge planning are associated with lower 30-day risk-standardized readmission rates
Hansen *et al.* (2011)	Hospital patients safety climate	36,375 employees in 67 hospitals	There is positive association between lower safety climate and higher readmission rates for AMI and HF
Joynt, Orav, and Jha (2011)	Race and site of care (non-minority and minority)	Medicare beneficiaries (3.1 million in 2006–2008)	Black patients were more likely to be readmitted after hospitalization for AMI, congestive HF and pneumonia
Onukwugha *et al.* (2011)	Discharges against medical advice(AMA)	348,572 patients from nonfederal acute care hospitals in Maryland with CVD (Cardiovascular disease)	The percentage of patients who were readmitted was higher among AMA group versus non-AMA group

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

Table 5. Summary of papers from 1989 through 2010 related to readmission prediction.

Author	Dates	R/P	Readmission definition	Diagnosis	Sample group	Readmission rate	Method	Significant factors
Allaudeen *et al.* (2010)	Jun 2006 May 2008	R	30-days unplanned	General medicine patients	Sample size: 6805; The University of California, San Francisco Medical Center	17.0%	Multivariable generalized estimating equations	Black race, Medicaid as payer, High-risk medications, Comorbidities (CHF, renal disease, cancer, weight loss, iron deficiency anemia)
Allaudeen *et al.* (2011)	Mar 2008 Apr 2008	R	30-days	General medicine patients	Sample size: 164; University of California, San Francisco Medical Center	32.7%	Receiver-operating characteristic (ROC) curves	Older age, male sex, poor self-rated general health, availability of an informal caregiver, coronary artery disease, diabetes, hospital admission within last year, more than six doctor visits during the previous year
Almagro *et al.* (2006)	Oct 1996 May 1997	P	1-year	COPD	Sample size: 129; Acute care teaching referral center, Barcelona, Spain	58.1%	Multivariable logistic regression	Previous hospitalization for, COPD, hypercapnia at discharge, poorer quality of life
Beck *et al.* (2006)	Jan 1996 Dec 2000	R	30-days	Pediatric	Sample size: 334,959; pediatric population (age≤18) Canadian Institute for Health Information Discharge Abstract Database	3.4% 3.6% (discharged on Friday) 3.3% (discharged on Wednesday)	Multivariable logistic regression	Number of diagnoses; in-hospital complications; hospital admission within prior 6 months
	2008	R	30-days	Advanced liver disease	Sample size: 447; hepatology service at Indiana University Hospital and University of Colorado Hospital	20%	Multivariate analyses	End-stage liver disease scores; presence of diabetes; male gender
Boulding *et al.* (2011)	July 2005 June 2008	R	30-day risk standardized	AMI, HF, Pneumonia	Unit of analysis was hospital; AMI: 1798 hospitals; HF: 2561 hospitals; pneumonia: 2562 hospitals. Hospital Compare database by the US Department of Health and Human Services; HCAHPS patient satisfaction survey data	20% (for all clinical areas)	Logistic regression	Overall patient satisfaction for AMI, HF, pneumonia (negatively); patient satisfaction with discharge planning for HF (negatively)
Boult *et al.* (1993)	1984	R	4-year	Elderly people	Sample size: 5876; 70 years old and older; Longitudinal Study of Aging (LSOA) data	28.4%	Multivariate logistic regression	Age, gender, self-rated general health, availability of an informal caregiver, coronary artery disease, previous hospital admission, more than six doctors visit, diabetes
Capelastegui *et al.* (2009)	Jul 2003 Jun 2007	P	30-day admission-related & admission-unrelated	CAP	Sample size: 1,117; Galdako Hospital, Spain	7.3%	Cox proportional hazard regression models	Pneumonia related: treatment failure, instability factors upon discharge Pneumonia unrelated: age >65, Charlson index>2, Decompensated comorbidities
Demir *et al.* (2008)	1997-2004	R	All types	COPD, Stroke, CHF	Sample size: COPD: 696,911; stroke: 546,406; CHF: 533,439; The Department of Health in England's Hospital Episode Statistics	COPD: 39% stroke: 21% CHF: 36%	Coxian phase-type distribution fitting via maximum likelihood Bayesian classification	Optimal time windows: COPD: 45 days; stroke: 16 days; CHF: 39 days
Fleming and Haney (2013)	1999-2002	R	30-days	Hip fractures	Sample size: 41331; Medicare patients (≥65 years old); National Medicare and VA	18.3%	Logistic regression	Men, long inpatient stay, Elixhauser comorbidities

Glasgow *et al.* (2010)	Oct 2003 Sep 2008	R	30-days all-cause readmission to any VA hospital	General medicine patients	Sample size: 1,930,947; 32,819 AMA patients; specified in patients left AMA; Veteran Administration Hospital	11% (patients who discharged home) 17.7% (AMA patients)	Multivariable Cox proportional hazards model	Discharge AMA, age, income comorbidities (arrythmia, dementia, fluid disorder, MI, psychosis, non-White race
Goldfield *et al.* (2008)	2005–2006	R	15 days index admission related readmission to same & any hospital	All types	Sample size: 4,311,653; 249 Florida inpatient hospitals	6.% (15 days, same hospital) 7.9% (15 days, any hospital)	—	Reason for admission, severity of illness, extremes of age, presence of mental health diagnoses, substance abuse problems
Greenblatt *et al.* (2010)	1992-2002	R	30-days readmission to any hospital	Patients who had colectomy	Sample size: 42,348; Surveillence, Epidemiology, and End Results (SEER)-Medicare database (Age≥66)	11%	Multivariate logistic regression	Male, Asian/Pacific race, region, prior hospitalization, comorbidity, emergent admission, prolonged hospital stay, blood transfusion, ostomy, postoperative complication, discharge to SNF, hospital procedure volume (negatively)
Halfon *et al.* (2002)	Jan 1997 Dec 1997	P	31-day	All types	Sample size: 3,474; Centre Hospitalier Universitaire Vaudois, Switzerland	23%	Stepwise selection based on Wald statistic	Previous hospitalization, long LOS, high Charlson comorbidity index, surgical stay and low Charlson score (negative)
Hannan *et al.* (2003)	Jan 1999 Dec 1999	R	30-days CABG related statewide readmission	CABG	Sample size: 16325; New York State's Cardiac Surgery Reporting System	15.3%	Stepwise logistic regression	Older age, women, having larger body surface area, having a myocardial infarction, comorbidities (hepatic failure, dialysis), hospital annual surgery volume < 100, hospitals with high risk-adjusted mortality rates, discharge to SNF, longer LOS
Hansen *et al.* (2011)	2006–2007 (survey data); 2008 (readmission rates)	R	30-day risk-standardized	AMI, HF, pneumonia	Unit of analysis: hospitals, sample size: 67 hospitals. Patient Safety Climate in Healthcare Organizations survey data responses	–	Multiple regression	Hospital safety climate for AMI and HF (negatively).
Hasan *et al.* (2010)	Jul 2001 Jun 2003	R	30-days all-cause, to index or another hospital	General medicine patients	Sample size: 7287 (derivation), 3659 (validation); Multicenter Hospitalist Study data	17.5%	Multivariable logistic regression	Insurance type, marital status, having a regular physician, Charlson index, Physical Medical Outcomes, admissions in last year, LOS longer than 2 days
Hendryx *et al.* (2003)	1997	R	1-year statewide readmission	Psychiatric patients	Sample size: 1384; Harborview Medical Center, Seattle, WA Department of Social and Health Services, Mental Health Division database	8.2% (depression: 1.5%; bipolar disorder: 7.1%; schizophrenia: 16%; other: 8.8%)	Continuous variables: least-squares linear; categorical variables: Maximum-likelihood logistic multiple regression	Substance abuse, global assessment of functioning score, prior hospitalization or outpatient service use, Age, social support unreliability, activity of daily living dysfunction

(*Continued on next page*)

Table 5. (Continued)

Author	Dates	R/P	Readmission definition	Diagnosis	Sample group	Readmission rate	Method	Significant factors
Holloway and Thomas (1989)	1980	R	31-days all-cause	All types	Sample size: 2946; National Medical Care Utilization and Expenditure Survey data	9.5% (all-cause) 3.1% (linked) 6.1% (same-condition)	Multiple logistic regression	Very high risk or high risk condition group for the index stay, poor or fair health status, surgery during the index stay to a patient with health-related activity limitations
Jasti *et al.* (2008)	Feb 1998 Mar 1999	R	30-days CAP-related comorbidity-related	CAP	Sample size: 577; 7 hospitals in Pittsburgh, PA	12.00%	Multiple logistic regression	Low education level; unemployment; coronary artery disease; COPD
Keenan *et al.* (2008)	2002–2005	R	30-days all-cause	HF	Sample size: 567,447; Medicare Standard Analytic Files, Medicare Enrolment Database (Age≥65)	23.6%	Hierarchical logistic regression	Age, gender, 9 cardiovascular variables, 26 comorbidities
Krumholz *et al.* (2000)	1994–1995	R	6-months all-cause statewide readmissions	HF	Sample size: 1129 (derivation), 1047 (validation); Medicare patients (≥65 years old); 18 Connecticut Hospital	49% (all cause) 23% (HF-related)	Cox proportional Hazard models	Prior readmission within 1 year, prior heart failure, diabetes, creatinine level>2.5 mg/dL
Lagoe *et al.* (2001)	1998–1999	R	30-days unplanned same category diagnosis	CHF	Sample sizes: 465 (Crouse Hospital); 575 (St. Joseph's Hospital); 366 (Community General Hospital) New York Statewide Planning and Research Cooperative System	9% (Crouse Hospital) 10.8% (St. Joseph's Hospital) 11% (Community General Hospital)	Manual stepwise regression	Crouse Hospital: Secondary diagnosis of cardiomyopathy or renal failure, 60 to 69 years old, inpatient stays of 6 days or more. St. Joseph's Hospital: secondary diagnosis of renal failure and diabetes, 60 to 69 years old. Community General Hospital: secondary diagnosis of renal failure and diabetes
Lin *et al.* (2011)	Aug 2006 Dec 2008	P	30, 90, 180, and 360-days	acute stroke	Sample size: 2,657; community hospital in southern Taiwan	30-day, 10%; 90-day, 17%; 180-day, 24%; 360-day, 36%	Kaplan-Meier method; Cox proportional hazard models	age, previous stroke, atrial fibrillation, coronary artery disease, complications at the index hospitalization, longer length of stay, dependency at discharge
Luthi *et al.* (2004)	Jun 1995 Sep 1996	R	21-months	HF (LVSD)	Sample size: 611; Medicare database (Age≥65),	70.0%	Bivariate analysis	Receiving no or low dose ACEI, prior MI, history of heart failure, diabetes, elevated creatinine level
Luthi *et al.* (2003)	Jan 1999 Dec 1999	R	30-days all-cause	HF	Sample size: 1055; three Swiss academic medical centers	13.2%	Multivariate logistic regression	None of the quality of care factors were significant
Medress and Fleshner (2007)	Aug 2001 Aug 2006	R	30-days unplanned, to index or another hospital	Patients who had colectomy	Sample size: 202; Cedars-Sinai Medical Center, Los Angeles	19.0%	Median comparison with Wilcoxon nonparametric test; categorical variables' comparison: Fisher's exact test	No preoperative or surgical factor was associated with readmissions
Mudge et al. (2010)	Feb 2006 Feb 2007	P	6-months unplanned	All types	Sample size: 142; age≥50; had prior two or more hospitalizations; tertiary teaching hospital, Brisbane, Australia	39.0%	Multiple logistic regression	Chronic conditions, body mass index, depressive symptoms

Neupane *et al.* (2010)	Jul 2003 Apr 2005	P	90-days all-cause	CAP	Sample size: 717; 2 Canadian cities; age ≥ 65;	11.2%	Logistic regression	Male, Vitamin E supplement given
Onukwugha *et al.* (2011)	2000-2005	R	CVD-related, 7-day, 31-day, 180-day after discharge AMA, to the same hospital	CVD	Sample size: 348, 572; Maryland Health services Cost Review Commission	7-day: 2%; 31-day: 6%; 180-day: 14%	Generalized estimating equations regression	Discharge AMA, age, gender, insurance type, weekend discharge, HF, drug abuse, PTCA, race, residence, stroke, alcohol abuse, CABG
Philbin and DiSalvo (1999)	1995	R	1-year	CHF	Sample size: 42731; Black and White race; New York State Department of Health Statewide Planning and Research Cooperative System database	21.3%	Logistic regression	Black race, Medicaid/Medicare insurance, home healthcare services, comorbidities, Use of telemetry monitoring negative factors: rural hospital, discharge to SNF, echocardiogram, cardiac catheterization
Tsuchihashi *et al.* (2001)	Jan 1997 Dec 1997	R	1-year CHF-related	CHF	Sample size: 230; 5 institutions in Fukuoka, Japan	35.0%	Multivariate logistic regression	Prior CHF admission, LOS, hypertension, no occupation, professional support, poor follow-up visits
van Walraven and Bell (2002)	Mar 1999 Mar 2000	R	30-days unplanned	All types	Sample size: 2,403,181; Ontario Discharge Abstract Database	5.4%	Proportional Hazards Modeling	Discharge on Friday
van Walraven *et al.* (2010)	Oct 2002 Jul 2006	P	30-day unplanned	All types	Sample size: 4,812; 11 hospitals in Ontario	8% (Readmission & mortality rate)	Multivariable logistic regression	Length of stay (L), acuity of the admission (A), comorbidity of the patient (C), emergency department use (E)
Weiss *et al.* (2010)	—	R	30-days unplanned	Medical-surgical patients	Sample size: 162 nurse-patient pairs; 4 Midwestern hospitals, Age>18	–	Logistic regression	Readiness for Hospital Discharge Scale-Nurse version (inverse effect), age, medical type admission

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

Table 6. Focus of readmission prediction papers and common predictive factors, 1989 through 2010.

Paper	Age	Gender	Comorbidity	Length of stay	Specific diagnosis/ disease	Prior admissions	Race	Clinical	In-hospital process	Discharge process	Family/ support	Socio-economic	General health	Treatment	Admission process	Insurance	Quality of life
Allaudeen *et al.* (2010)	x	x	x	x			x	x		x			x		x	x	
Almagro *et al.* (2006)			x		x	x		x			x	x		x			x
Beck *et al.* (2006)	x	x		x		x			x								
Boult *et al.* (1993)	x	x				x	x				x	x	x				
Capelastegui *et al.* (2009)	x		x	x	x	x		x	x				x	x			
French *et al.* (2008)	x	x	x	x													
Glasgow *et al.* (2010)	x	x	x				x					x					
Greenblatt *et al.* (2010)	x	x	x	x	x	x	x	x	x	x	x	x		x	x		
Halfon *et al.* (2002)	x	x		x	x	x				x				x			
Hannan *et al.* (2003)	x	x	x	x	x		x	x	x					x		x	
Hasan *et al.* (2010)			x	x		x					x					x	
Heggestad and Lilleeng (2003)				x													
Hendryx *et al.* (2003)	x	x		x	x	x	x	x			x	x	x				x
Hofer and Hayward (1995)																	
Holloway and Thomas (1989)		x					x	x	x		x	x	x			x	
Jasti *et al.* (2008)	x	x	x	x	x	x	x	x		x	x	x	x			x	
Keenan *et al.* (2008)	x	x	x		x			x									
Krumholz *et al.* (2000)	x	x		x	x		x	x	x	x			x				
Lagoe *et al.* (2001)	x	x	x	x	x		x			x	x	x	x				

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

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

Tables 7 and 8 summarize these hospital and database studies, respectively. The latter type of study generally had larger sample sizes because of their wider service regions. A focus on heart failure patients is even more common in database studies, as seen in Hofer and Hayward (1995); Keenan, Normand, and Lin (2008); Krumholz *et al.* (2000); Luthi *et al.* (2003); and Philbin and DiSalvo (1999). In addition, two studies used hospitals rather than patients as the unit of analyses. In one, Boulding *et al.* (2011) investigated the relationship between patient satisfaction survey results aggregated at the hospital level and 30-day hospital readmission rates. In the other, Hansen *et al.* (2011) explored the relationship between 30-day risk-adjusted readmission rates and patient safety climates, assessed through employee surveys.

4. Discussion

4.1. Challenges and opportunities for industrial engineers

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

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

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

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

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

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

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

Table 7. Summary of hospital-level studies.

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

Veterans Affairs hospitals, potentially limiting the generalizability of the results.

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

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

Although many studies identified factors associated with readmissions, most did not draw conclusions about causality nor offer guidelines on how to optimize any particular intervention to reduce readmission rates (Balaban *et al.*, 2008; Bell *et al.*, 2009; Chen *et al.*, 2010; Krumholz *et al.*, 2002; van Walraven and

Table 8. Summary of database-level studies.

Paper	Location/Type	Sample Size	Notes
Beck *et al.* (2006)	Canadian Institute for Health Information database	334,959	Pediatric patients
Boult *et al.* (1993)	Longitudinal Study of Aging (LSOA)	5,876	Elderly people 70 years old and older
French *et al.* (2008)	National Medicare and Veterans Health Administration (VHA) facilities	41,331	Medicare Elderly veterans
Glasgow *et al.* (2010)	129 acute care Veterans Administration hospitals	32,819 patients 1,930,947 admissions	Left against medical advice veterans
Greenblatt *et al.* (2010)	Centers for Medicaid and Medicare Services	42,348 patients	Colectomy
Goldfield *et al.* (2008)	249 Florida inpatient hospitals	4,311,653 admissions	
Hannan *et al.* (2003)	New York State hospitals	16,325 patients	CABG surgery
Hasan *et al.* (2010)	Multi Center Hospitalist Study data (designed in six academic medical centers in the US)	10,946 patients	General medicine
Hofer and Hayward (1995)	190 hospitals in the statewide Michigan Inpatient Database	603,959 patients	HF, gastrointestinal, neuologic, pulmonary disease
Holloway and Thomas (1989)	1980 National Medical Care Utilization and Expenditure Survey data	2206 patients	
Keenan *et al.* (2008)	2002-2005 Medicare claims data from the Medicare Enrollment Database	>1 million admissions	HF
Krumholz *et al.* (2000)	18 Connecticut Hospitals	2176 patients	HF 65+
Luthi *et al.* (2003)	50 community hospitals in Colorado, Connecticut, Georgia, Oklahoma, and Virginia	2943 patients	HF
Onukwugha *et al.* (2011)	Maryland Health Services Cost Review Commission Database	348,572 patients	CVD
Philbin and DiSalvo (1999)	New York State Department of Health	42,731 patients	CHF
van Walraven and Bell (2002)	11 hospitals (6 university-affiliated, 5 community) in Ontario	4812 patients	Medical or surgical
van Walraven *et al.* (2010)	Discharge Abstract Database (DAD), which records all discharges from Ontario hospitals	2.4 million patients	Non-elective admissions adult

Bell, 2002). For example, van Walraven and Bell (2002) found that readmission risk may decrease with better discharge summary availability during post-discharge visits, but were unable to determine how dissemination of discharge summaries to follow-up physicians might avoid readmissions.

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

Despite the heightened focus on preventing readmissions, it is not always clear if, where, and why readmission rates are improving. Ross *et al.* (2010), for example, found no reduction in readmission rates nor significant differences in rates among hospitals from 2004 through 2006 for Medicare beneficiaries discharged after hospitalization for heart failure. Thus, development and use of methods to better estimate readmission rates and causality would seem useful as well. Similarly, performance measures to evaluate intervention strategies (e.g., compliance, frequency, coverage) are needed to monitor their effectiveness. Given the complexities, human interactions, and interdependencies of multiple factors, exploring various socio-technical analyses that better address the human factor seems especially appropriate. System dynamics models also might be useful here, possibly including analysis of various financial and public reporting incentives and of the introduction and optimal design of accountable care organizations and other new integrated delivery system concepts. In summary, numerous opportunities exist for industrial engineering and operations research methods to complement, support, and extend the hospital readmissions work done to date, which is now mostly being conducted within other disciplines. Given the importance of this problem across the entire United States healthcare system, it is appropriate for industrial engineers to begin to apply their expertise to this challenging area.

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