University of Alberta

Outcomes in General Internal Medicine Inpatients

by

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Abstract

This thesis describes 3 thematically linked projects exploring outcomes for hospitalized medical patients. Project 1 examines the accuracy of various models in predicting post-discharge outcomes in patients with heart failure (HF). Project 2 explores the relationship between teaching and non-teaching services on clinical outcomes for patients admitted to general internal medicine (GIM) services. Using the risk adjustment model developed in project 1 and the covariates identified in project 2, project 3 explores whether post-discharge outcomes differed for weekend vs. weekday discharges for HF patients in teaching vs. non-teaching hospitals.

The work from this thesis confirms that post-discharge adverse outcomes such as readmission or death are common in Alberta, are affected by multiple factors, and are not easily predicted using currently available models. Future efforts to identify and intervene in patients at high risk of readmissions will need to consider factors beyond those we studied if they are to be successful.

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Chapter 1: Introduction

i) Readmissions are a significant contributor to hospital costs

Hospitalized patients are a major driver of health care costs. In 2010, an estimated $56.3 billion (29.1% of total health care costs in Canada) was spent on hospitalizations representing the largest single category of health care expenditures.(1) Readmissions are a significant contributor to hospitalizations with 5-33% of adult medical-surgical patients being readmitted within a month, depending on the diagnosis.(2-5) In the United States, readmissions within 30 days account for one fourth of Medicare expenditures for inpatient care with estimates that $17.4 billion was spent on 19.6% of Medicare patients readmitted within 30 days in 2004.(4) In Canada, readmissions within 30 days cost the health care system an estimated $1.8 billion in 2011.(6)

Medical patients account for a large proportion of readmissions. In 2012, the combined overall readmission rate for medical, surgical, pediatric and obstetric patients in Canada was 8.5%, with medical patients accounting for 64.9% of those readmissions. (6). Readmission rates to general medicine services have ranged from 12.2 to 17.5% (7-11) with one study showing a readmission rate as high as 32.5% (2). Heart failure (HF) is the most common cause of readmission in both Canada (6) and the United States.(4) In patients with an index diagnosis of HF, one in five patients (21%) was readmitted within 30 days in Canada.(6) The Canadian Cardiovascular Outcomes Team found a 30 day readmission rate of 6.5-10.4% in patients with a discharge diagnosis of HF depending on the province.(12) In Edmonton, a 20% combined 30-day readmission and mortality rate (13) was found for patients presenting to the emergency department with acute HF.

ii) Hospital readmissions are used as a marker of hospital performance and quality of care

Because readmissions are common and pose a significant burden on the healthcare system, it has attracted considerable attention from government and healthcare funders to use it as an indicator of quality of care. Indeed, readmissions after hospital discharge are widely used as a marker of suboptimal inpatient care and/or care transition back to the community (10, 14) although a consistent link between early unplanned readmissions and suboptimal quality of care has not been well established.(7, 15) In the United States, the Centers for Medicare and Medicaid Services (CMS) currently reports hospital readmission rates for acute myocardial infarction, HF and pneumonia and in 2013 have begun adjusting payments to hospitals based on hospital performance for these conditions.(16, 17) While CIHI tracks 28 day readmission rates for acute myocardial infarction and pneumonia as health performance indicators in medical patients (18), there are currently no payment adjustments to hospitals in Canada based on these readmission rates.

The focus on using hospital readmissions as a reflection of hospital quality of care should be aimed at addressing preventable readmissions as not all readmissions are preventable. However, the definition of what constitutes a preventable readmission is not well established leading to a wide range of reported avoidable readmission rates in the literature.(19-21) Van Walraven reported a range from 5-79% of readmissions from 38 studies deemed to be avoidable (21) while Yam looked at 48 studies and reported a range of 9-59%.(19) Both studies found the lack of a consistent definition for an avoidable readmission, different methods of data collection and differing methods of data analysis. In the Canadian context, a recent study of 11 teaching and community hospitals in Ontario found a 6-month unplanned readmission rate of 13.5% of which 16% of those readmissions were deemed potentially avoidable. (22) Due to the lack of a consistent definition of what constitutes an avoidable readmission, the majority of studies published in the area of readmission research continue to focus on all-cause readmissions as the outcome measure.

iii) Risk prediction models for post-discharge outcomes (readmission or mortality)

Interest in the arena of predictive scoring systems has increased as a means by which to identify patients at greatest risk of readmissions and thereby target interventions to these individuals and as a means of risk adjusting quality metrics such as readmission rates for comparing between hospitals. Various statistical models have been derived to predict readmission and mortality rates which take into account a variety of factors including but not limited to clinical characteristics, disease severity, comorbid conditions, sociodemographic factors, hospital course, laboratory measures, and discharge medications (8, 23-30) Some require area-specific information such as community-specific rates of admissions or neighbourhood-specific socio-economic indices which is not readily accessible(26, 27), special software(26-28) or require the use of health surveys(8). The LACE index is one such predictive scoring system derived and validated in a Canadian population of both medical and surgical patients to predict 30 day risk of readmission and death(29). The Centers for Medicare & Medicaid Services (CMS) currently uses administrative datasets which include 24 variables to estimate 30 day mortality rates after admission (thus including deaths during the index hospitalization)(30) and 37 variables to estimate 30 day readmission rates(24) after discharge for patients with HF. A separate model uses 31 variables to predict 30 day readmission risk for acute MI (31) and a model of 39 variables is used to predict 30 day readmission risk for pneumonia (25). A review of 26 unique readmission risk prediction scoring models found that most models used for comparative or clinical purposes performed poorly.(32)

iv) *Factors* that may affect readmission rates and interventions

A variety of factors have been shown to affect readmission rates including patient age, sex (33), previous admission within 30 days (34), increasing number of comorbidities (35), emergent admission (29), diagnostic group and case mix (4, 15, 36), severity of illness and complexity of disease (15, 33, 36)', length of stay during index hospitalization (29, 33), functional ability, and sociodemographic factors (37, 38). This has led to intervention studies targeted at high risk patients including increased multidisciplinary ward rounds (11), comprehensive discharge planning (39-42), targeted care bundle (43) and intensive post-discharge follow-up (44, 45) with mostly favourable results. In systematic reviews of various interventions discharge interventions, multi-component interventions that combined pre and post-discharge elements seemed to be more effective in reducing readmissions.(46, 47) The application of these interventions, however, may be affected by several factors including the geographical location of healthcare providers (rural versus urban), patient's residence (which could affect access to services), availability of healthcare professionals, socioeconomic factors beyond simply the cost of medications and healthcare providers which are less important in countries where health care access is universal, to name a few.

v) Hospital teaching status and patient outcomes

The role of teaching hospital status has also been an area of interest as it relates to quality of care and outcomes. Teaching hospitals have an important role to play in the health care system. They are involved in the education/training of future clinical providers, provide care to more seriously ill patients, offer more sophisticated technologies and deliver specialized services and are often involved in research activities.(48) Studies (49-51) suggest that care in teaching hospitals is more costly than that provided in non-teaching ones, although other studies have not confirmed this (52). More seriously ill patients and those with more complex disease are often admitted to academic institutions where care is provided on a teaching service (51, 53-55) by trainee physicians with varying degrees of experience overseen by teaching faculty. In addition, quality of care may differ between teaching and non-teaching hospitals (48, 50, 51, 53, 56, 57, 58). While most studies in fields outside of general internal medicine suggest that patient care is generally of similar quality when delivered by trainee physicians as by faculty (59), it is unclear whether outcomes are better or worse for patients cared for on teaching compared to non-teaching inpatient clinical services.

vi. The Weekend effect

Weekend admissions to hospital can result in increased inpatient mortality rates for several medical conditions including stroke, pulmonary embolism, atrial fibrillation, myocardial infarction, heart failure, chronic obstructive pulmonary disease among others (60-67). This phenomenon was found for both non-elective (60, 62) and elective admissions (68) and in various settings including the intensive care unit (ICU) (69-71), internal medicine wards (72) and in teaching hospitals (73). A large Canadian study of all acute care admissions from emergency departments in Ontario over a 10 year period found that, of the top 100 conditions that caused the most deaths, 23 were associated with a statistically significant higher mortality rate if admitted on a weekend than if admitted on a weekday (60).This finding has been termed the "weekend effect". Potential reasons for this effect include reduced staff and physician coverage (61), reduced availability of invasive medical procedures (74, 75) and patient characteristics (64).

While hospital discharges may be delayed over the weekend (76, 77), whether patients discharged on weekends have poorer clinical outcomes has been less well studied. A study of all patients discharged from Ontario hospitals over a 10 year period found that patients discharged on Fridays had an increased risk of death or non-elective hospital readmission within 30 days after discharge but had a decreased risk if discharged on the weekend.(78) Potential reasons for increased risk if discharged on Friday included less medically stable patients being discharged, incomplete discharge preparation resulting from increased demands on both clinicians' and hospital staff's time from multiple discharges, or a delay in implementation of social services over the weekend (78). Reasons for decreased risk for weekend discharges were not explored but possibilities include more medically stable patients, those with less severity of illness or those not requiring social services in the community, being discharged on the weekend. A study looking at HF patients in the Get with The Guidelines-Heart Failure registry found that patients discharged on the weekend had significantly lower odds of complete discharge instructions and documentation of left-ventricular ejection fraction.(63) When associations between discharge day of the week and 60 and 90 day death or rehospitalisation rates were studied, no differences were found for HF patients in 259 US hospitals that were part of the OPTIMIZE-HF registry (79). Due to the possible negative patient outcomes that may occur depending on day of the week patients are discharged, this remains an area ripe for research.

This thesis will cover three projects aimed at assessing post-discharge outcomes in medical patients (general internal medicine or heart failure). The first project will assess the ability of a new readmission risk calculator called the LACE index to predict readmissions in heart failure patients and will compare it to other models currently endorsed for this purpose. The second project will be a systematic review analysing whether differences exist in outcomes between patients treated on internal medicine services where care is provided by teaching versus non-teaching teams. The final project will focus on differences in outcomes depending on the day of discharge for patients with heart failure in teaching and non-teaching hospitals in Alberta.

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Chapter 2

Predicting the risk of unplanned readmission or death within 30 days of discharge after a heart failure hospitalization[1]

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[1] *A version of this chapter has been published. Au AG, McAlister FA, Bakal JA, Ezekowitz J, Kaul P, van Walraven C. Predicting the risk of unplanned readmission or death within 30 days of discharge after a heart failure hospitalization. Am Heart J. 2012 Sep;164(3):365-72.*

Heart failure (HF) carries a very high risk of readmission within 30 days;(1, 2) HF is also the most common reason for readmissions after any hospital discharge, regardless of the reason for the original hospitalization.(3) Given the recent proposal within the Affordable Care Act to penalize hospitals with high 30 day readmission rates, there is now substantial interest in evaluating this outcome. However, in order to fairly compare performance between hospitals and/or providers there is a need for prediction models which can be used for risk-adjustment of observed readmission rates to take into account differences in case mix and other factors which drive readmission rates.

Multiple factors increase the chance of readmission or death in HF patients discharged from hospital,(4, 5) and several models have been proposed for predicting post-discharge risk in HF patients.(2, 6-13) The risk prediction models currently endorsed by the Centers for Medicare and Medicaid Services (CMS) use administrative datasets and include 24 variables to estimate 30 day mortality rates after admission (thus including deaths during the index hospitalization)(13) and 37 variables to estimate 30 day readmission rates after discharge(2). Although models that include clinical variables improve the prediction of mortality over administrative data-based models, they have not been shown to predict hospital readmissions any better than the CMS-endorsed administrative data models. (6, 10) However, the CMS models predict either mortality in the first 30 days *after admission* or readmission in the first 30 days *after discharge*, and these measures correlate poorly with each other and with quality of care.(14) Indeed, mortality is a competing risk in any study of readmission rates since patients who die are not eligible for readmission. We are not aware of any HF-specific prediction rule for the composite outcome of most interest to clinicians and health system planners at the time of discharge, namely "unplanned readmission or death within 30 days after discharge".

A recent prospective cohort study of approximately 4800 patients discharged after medical or surgical hospitalizations (218 of whom had HF) described the 4 item LACE index for predicting the composite outcome of unplanned readmission or death in the first 30 day after discharge (c-statistic 0.68).(15) The LACE index incorporates length of stay for the index hospitalization (L), acuity of admission (A), Charlson comorbidity score (C), and emergency room utilization in the prior 6 months (E). An extension of the LACE (the LACE+) index incorporates age and items unique to Canadian administrative databases (such as the Canadian Institute for Health Information Case Mix Groupings and number of hospital days awaiting alternate level of care arrangements) and has recently been shown to predict death or unplanned readmission within 30 days with greater discrimination (c statistic 0.77) than the LACE index.(16) As the majority of the medical hospitalizations in the LACE studies were for acute coronary syndromes and cancer, the performance of these indices in patients with HF is unknown. In this study, we explore which variables available in administrative data are predictive of the composite outcome of readmission or death in the first 30 days after discharge and compare the performance of the CMS-endorsed models, the Charlson model, and the LACE/LaCE index in predicting 30 day post discharge outcomes in HF patients.

Methods:

Study Setting:

The province of Alberta has a single payer, government-funded health care system that provides universal access to over 3.7 million people for hospital, emergency department, and physician services. This study received ethics approval from the Health Ethics Research Board at the University of Alberta.

Data Sources:

This study used de-identified data from four administrative databases maintained by Alberta Health to create our study cohort including: (1) the Discharge Abstract Database, which records the admission date, discharge date, most responsible diagnosis, and up to 25 other diagnoses for all acute care hospitalizations; (2) the Ambulatory Care Database, which records all patient visits to hospital-based physicians' offices or Emergency Departments with coding for of up to 10 conditions between 2000 and 2009; (3) the Practitioner Claims Database, which tracks all physician claims for outpatient services and includes up to 3 diagnoses per encounter; and (4) the Alberta Health Care Insurance Plan Registry, which tracks vital status of all Albertans.

Study Cohort:

We identified all adult Albertans discharged from hospital between April 1, 1999 and March 31, 2009 with a diagnosis of HF (ICD-9-CM code

428.x or ICD-10 code I50.x) listed in any diagnostic field (17-19). The accuracy of these ICD codes for HF (specificity 97% to 99%, positive predictive value 91% to 94%) have been previously validated against chart audit in Alberta (19) and other Canadian provinces (18).

We randomly selected one episode of care per patient for this analysis. Patients transferred to another inpatient service or discharged to another acute care or rehabilitation hospital were excluded. Patients discharged to long-term care facilities were included.

Predictive Indices:

For each model that we evaluated, patient comorbidities were identified using ICD-9 and ICD-10 codes from the index hospitalization and any hospitalizations in the 12 months prior. From these codes, the Charlson index was computed(20). To generate the CMS models, we used both the covariate weights reported in the original papers (2, 13) and fit logistic regression models using the variables included in each model.

The LACE index consists of four independent components including length of hospital stay ("L"), acuity of admission ("A"), comorbidity of patient quantified using the Charlson comorbidity index ("C"), and emergency department utilization measured as the number of visits in the six months prior to admission ("E"). Points assigned to each of these four parameters are summed with a maximum possible LACE score of 19 (15).

The LACE+ index includes all of the LACE variables as well as age and items unique to Canadian administrative databases (such as the

Canadian Institute for Health Information Case Mix Groupings and number of hospital days awaiting alternate level of care arrangements). As we wanted to test administrative-data based models which could be used for risk adjustment for HF patients in a wide variety of settings (not just in Canada), we tested the LaCE index (which excluded acuity of admission since virtually no HF admissions are elective but included age given its importance in the LACE+ index, but excluded other elements included in the LACE+ which are specific to Canadian datasets).

Analysis:

Our primary outcome was death or unplanned readmission in the first 30 days after hospital discharge. Unplanned readmissions were defined as those occurring through the emergency room (as distinct from those which were flagged as “elective” in the Discharge Abstract Database file). We measured the ability of the Charlson score (20), the LACE score (15), the LaCE score, and the CMS-endorsed Krumholz (13) and Keenan (2) scores to discriminate between those with and without an outcome in the first 30 days after discharge using the c-statistic (with 95% bootstrap confidence intervals). We used the Net Reclassification Index (NRI) (21) to estimate the proportion of correct (fitted risk of event being higher in those who had events and lower in those without events) minus incorrect reclassifications (i.e., those with higher predicted risk and no event or those with lower predicted risk and an event) for each model over comparator models for our primary outcome.

Using the entire set of variables generated for all models, we undertook a random forest analysis (22). In this analysis, classification trees were generated from a bootstrap sample of the data. Each tree provided a classification based on the candidate variables. Using this set of trees, the ability of each variable to discriminate between individuals who did and did not have an event was evaluated and weighted according to the overall quality of the tree. The summary of individual variable importance is given by a Gini score, which gives an estimate of the loss in model accuracy if the variable is not included. Additional models were examined utilizing the variables based on the random forest models

In two sensitivity analyses, we repeated analyses after limiting the study population to: (1) patients for whom HF was the most responsible diagnosis; and (2) only those patients with a most responsible diagnosis of HF who were over age 65 (since the Krumholz and Keenan prediction models were derived in elderly Medicare patients). For both of these sensitivity analyses, we randomly sampled one hospitalization from each subgroup that fit this definition. We also explored what the optimal cutpoint for the LACE score should be in HF patients to discriminate high vs. low risk using Receiver Operating Characteristic curves and determined the proportion of HF patients readmitted/died within 30 days of discharge who had high LACE scores using this ROC-generated cutpoint value. All analyses were conducted using R version 2.13.2 (www.R-project.org, Vienna, Austria)

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Results:

During our study, 59 652 adults in Alberta were discharged after being hospitalized with a diagnosis of HF listed as either the most responsible or a secondary diagnosis. Death or unplanned readmission occurred in about one fifth of patients in the first 30 days following discharge (Tables 2.1 and 2.2), with the vast majority of these events being readmissions (and 18.6% of the readmissions were for HF as most responsible diagnosis). Patients who were subsequently re-admitted or had died within 30 days of discharge were older and had a greater number of comorbidities (all $p < 0.0001$, Table 2.1). Of note, the LACE scores in this cohort were skewed to the right (Table 2.1). Although receiver operating curve analysis suggested that the optimal cutpoint for LACE in patients with HF is 14, of those patients who died or had an unplanned readmission within 30 days of hospital discharge in our cohort, 60% had LACE scores of 14 or greater and 40% had LACE scores less than 14 (OR

= 1.71, 95%CI 1.64 to 1.78 for risk of unplanned readmission/death in HF patients with LACE score of 14 or greater).

None of the 5 administrative-data based models had high discriminative ability for "unplanned readmission or death within 30 days of discharge" with c-statistics ranging between 0.54 and 0.61 (Table 2.3) even in those with a most responsible diagnosis of HF and in the elderly subcohort. All of the models exhibited only moderate discrimination for a variety of outcomes commonly analyzed in patients hospitalized for HF (Table 2.3).

Compared to the Charlson score, we found that neither CMS model substantially improved the prediction of our primary outcome (net reclassification improvement 2.6% [95% CI 0.5% to 4.6%] for the Keenan model and 0.06% [95% CI 0.03% to 0.10%] for the Krumholtz model) – Table 2.4. On the other hand, the LACE index exhibited a 12.6% net reclassification improvement (95% CI 10.5% to 14.7%) for our composite endpoint over the Charlson score and a 15% net reclassification improvement (95% CI 12.9% to 17.1%) over the Keenan model. The LaCE index demonstrated a net reclassification improvement of 4.5% (95%CI 2.4% to 6.5%) compared to LACE, 20.5% (95% CI 18.4% to 22.5%) over using the Charlson score alone, and a 19.1% improvement (95% CI 17.1% to 21.2%) over the Keenan model for "unplanned readmission or death in the first 30 days after discharge" – Table 2.4.

Random forest plot analysis confirmed that the 4 elements of the LaCE score (age, index length of stay, number of emergency room visits in prior 6 months, and Charlson score) had the strongest influence on our primary outcome (Figure 2.1). Of note, as 94% of those patients with a diagnosis of HF in any diagnostic field during their index hospitalization and 98% of those with a most responsible diagnosis of HF were admitted through the emergency room the “acute admission” item in the LACE index was less useful for post-discharge prediction in patients with HF.

The fitted LaCE model was associated with an odds ratio of 0.99 (95%CI 0.998-0.999) for each additional day in hospital during the index hospitalization while the other variables were positively correlated. For example, the aOR was 1.11 (95%CI 1.09-1.13) for each decade of age each point in the Charlson score was associated with an aOR of 1.09 (95%CI 1.09-1.10), and each prior visit to the emergency room was associated with an aOR of 1.20 (95%CI 1.18-1.22).

Discussion:

This is the first study to examine the discriminative ability of the CMS-endorsed prediction models and the LACE/LaCE indices in a broad heart failure population and for the composite outcome of “death or unplanned readmission within 30 days of discharge”. Although LACE and LaCE demonstrated only moderate discrimination for predicting 30 day unplanned readmission or death, thereby limiting their use for patient-level prediction, both indices were significantly better able to predict the composite of death or unplanned readmissions within 30 days of discharge than the Charlson or either of the CMS models. Based on the present study we believe that the 4 variable LaCE model (length of hospital stay, age in years, Charlson score, and number of emergency visits in past 6 months) is worthy of additional validation studies as a model to risk adjust post-discharge outcome rates for comparisons between hospitals (or in the same hospital over time).

Increasing age is an important predictor of readmissions and death and is used in many models, including the CMS-endorsed models (2, 6, 7, 10, 13, 23, 24). However, the CMS models do not include either length of index hospital stay or the number of ED visits, both of which we have shown provide additional information not captured by comorbidity indexes such as the Charlson. For example, ED visits may be a surrogate marker for social factors. A recently published model (7) from one major urban hospital in the U.S. included factors such as the number of home address changes, use of Medicare, and health behaviours (such as cocaine use and missed clinic visits) in their model and found better discrimination (c-statistic 0.72) for predicting readmission in patients discharged after a most responsible diagnosis of HF. While some may argue that many non-patient and non-modifiable factors (such as hospital size, nursing:census ratios, physician mix, local and/or individual socioeconomic factors, the availability of home support and/or health care resources) drive length of stay and thus should not be included in a risk adjustment model, we would contend that these same non-patient factors drive admission thresholds and readmission rates and thus are appropriate to included in risk adjustment models.(25,26) Certainly, including length of stay appears to improve the predictive ability of post-discharge models, although this should be evaluated in US Medicare data since length of stay in the US is significantly shorter than in Canada.(27)

The c-statistics in our study for the CMS models are very similar to those reported in the original cohorts in which they were developed (for example, the c-statistic for 30 day unplanned readmissions was 0.59 in our cohort versus 0.60 in Keenan's original study) or in a recent study focusing on older patients from the "Get with the Guidelines-Heart Failure" registry (0.59) (10). This confirms the generalizability of these models, even though the CMS models were derived from Medicare patients aged 65 and over with a most responsible discharge diagnosis of HF and even though their 30 day readmission rates (24%) were higher than those in our study. However, it is important to note that the outcome the Krumholz model was developed for was death within 30 days of admission (ie. **not 30 days after discharge**) and thus is not directly comparable to the LACE or LaCE models. Our mortality rates in the first 30 days after discharge (4.3% after most responsible diagnosis of HF) were very similar to those reported for 2004 US Medicare data (4.4%).(2) We included the CMS Krumholz model in this study even though it was developed for a different endpoint in order to ascertain its usefulness for the composite outcome of death/readmission within 30 days of hospital discharge which is a metric increasingly being cited by policy makers and funders (and is included in the Affordable Care Act) as a means to judge hospital (and physician) performance.(28)

Although our data is drawn from a single payer health care system with universal access to services and thus complete capture of all outcomes, and our results are robust across a variety of sensitivity analyses, there are some limitations to our study. First, we examined all-cause readmissions rather than HF readmissions. However, readmissions in patients with HF are often due to comorbid conditions(5) and it is difficult to disentangle the true factor triggering readmission when a patient presents with multiple diagnoses. Second, we evaluated models based on administrative data in order to find which models are most appropriate for risk adjustment in large datasets (either to compare outcomes between different sites or in the same site over time) and not for individual patient prognostication. Third, as our LaCE index represents a de novo model it will require validation in another HF-specific dataset since the LACE+ Study(16) was an unselected sample of 500,000 medical and surgical hospitalizations and both our study and the LACE+ Study were done in Canada while length of stay for HF hospitalizations in the United States is substantially shorter.

In conclusion, we have demonstrated that 4-component models using administrative data including index hospital length of stay to estimate 30-day death or unplanned readmission risk after discharge in patients with HF are as discriminative as more complicated models. Although neither the LACE nor the LaCE models are sufficiently accurate to be used to target resources to those most likely to benefit at hospital discharge, they can be used to risk adjust outcomes between hospitals (or in the same hospital over time) and thereby assist in assessing health system performance in heart failure. Further research is needed to validate the LaCE model in US datasets and to develop a prediction model based on clinical variables available at the bedside to assist clinicians in identifying which patients are most at risk in the immediate period after discharge to reduce risk of death and/or unplanned readmission.

Table 2.1 Baseline characteristics at time of discharge from index heart failure hospitalization

	Hospitalized with HF in any diagnostic field n=59 652		
	No unplanned re-admission/ death within 30 days n=48453	Unplanned re-admission or death within 30 days n=11199	p-value
Age at index discharge, yr, mean (SD)	75.5 (12.8)	77.2 (12.1)	<0.001
Female (%)	24408 (50.4)	5550 (49.1)	0.02
Charlson comorbidity index score (mean, SD)	4.2 (2.1)	4.8 (2.6)	<0.001
Prior myocardial infarction (%)	13836 (28.6)	3383 (30.2)	0.0005
Peripheral Vascular Disease (%)	4913 (10.1)	1455(13.0)	<0.0001
Cerebrovascular disease (%)	4643 (9.6)	1259 (11.2)	<0.0001
Dementia (%)	4736 (9.8)	1340 (12.0)	0.04
chronic obstructive pulmonary disease (%)	16758 (34.6)	4423 (39.5)	<0.0001
connective tissue disease (%)	1648 (3.4)	409 (3.7)	0.2
mild liver disease (%)	845 (1.7)	244 (2.2)	0.002
Diabetes (%)	14756 (30.4)	3752 (33.5)	<0.0001
severe liver disease (%)	389 (0.8)	143 (1.3)	0.27
Cancer (%)	4103 (8.5)	1740 (15.5)	<0.0001
AIDS (%)	17 (0.03)	8 (0.04)	0.02
Proportion hospitalized at least once in prior 6 months (%)	17502 (36.1)	5561 (49.7)	<0.0001
Proportion visiting ED at least once in prior 6 months (%)	30155(62.2)	8002 (71.5)	<0.0001
Length of Stay in those discharged alive, Median (IQR)	10 (6-19)	11 (6-20)	<0.0001

Discharge disposition *	n=32749	n=7189	<0.0001
-home	20781 (63.5)	3949 (54.9)	
-home with homecare	7801 (23.8)	2029 (28.2)	
-Long Term Care	3962 (12.1)	1047 (14.6)	
-hospice/other	205 (0.6)	164 (2.3)	
LACE score, Median (IQR)	13 (11-15)	14 (12-16)	<0.0001

* only available since 2002

Table 2.2. Outcomes in the first 30 days after discharge

30 day outcomes after discharge	Hospitalized with HF in any diagnostic field (n=59 652)	Hospitalized with Most responsible diagnosis of HF (n=23 454)	Hospitalized with most responsible diagnosis of HF and age ≥ 65 (n= 19 764)
Death	3041 (5.1)	1003 (4.3)	1003 (4.7)
Unplanned readmission	9419 (15.9)	4344 (18.5)	3722 (18.8)
Death or unplanned re-admission	11199 (18.8)	4865 (20.7)	4201 (22.1)

Table 2.3. Discriminative statistics for various models

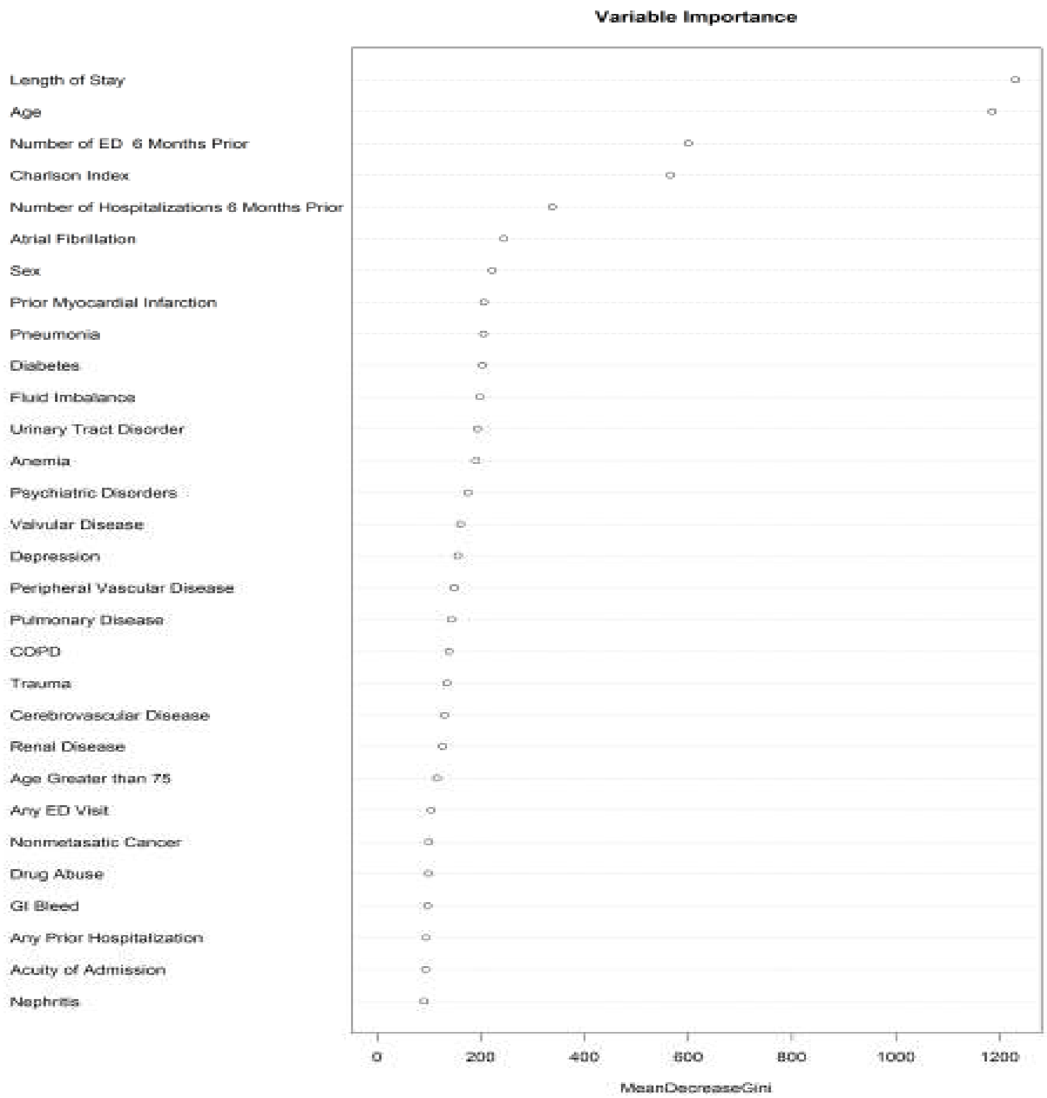
Models	Hospitalized with HF in any diagnostic field	Hospitalized with Most responsible diagnosis of HF	Hospitalized with most responsible diagnosis of HF and age ≥ 65
For outcome of 30 day unplanned readmission or death after hospital discharge			
Charlson (95% CI)	0.57 (0.56-0.57)	0.55 (0.54-0.56)	0.55 (0.54-0.56)
Krumholz (95% CI)	0.60 (0.60-0.61)	0.59 (0.59-0.60)	0.59 (0.58-0.60)
Keenan (95% CI)	0.61 (0.61-0.62)	0.60 (0.58 - 0.60)	0.59 (0.58-0.59)
LACE (95% CI)	0.59 (0.58-0.59)	0.59 (0.58-0.60)	0.58 (0.58–0.59)
LaCE (95% CI)	0.61 (0.61-0.62)	0.61 (0.60-0.61)	0.60 (0.59-0.61)
For outcome of 30 day mortality after hospital discharge			
Charlson (95% CI)	0.62 (0.61-0.63)	0.59 (0.58-0.60)	0.58 (0.57-0.60)
Krumholz (95% CI)	0.71 (0.70- 0.71)	0.68 (0.67-0.70)	0.66 (0.65–0.68)
Keenan (95% CI)	0.72 (0.71-0.73)	0.69 (0.68-0.71)	0.67 (0.66-0.69)
LACE (95% CI)	0.61 (0.60-0.62)	0.61 (0.60–0.63)	0.60 (0.59-0.62)
LaCE (95% CI)	0.66 (0.65-0.67)	0.66 (0.65-0.68)	0.65 (0.64-0.66)
For outcome of 30 day unplanned readmission after hospital discharge			
Charlson (95% CI)	0.55 (0.55-0.56)	0.55 (0.54–0.56)	0.54 (0.54–0.55)
Krumholz (95% CI)	0.58 (0.58-0.59)	0.58 (0.58-0.59)	0.58 (0.57-0.59)
Keenan (95% CI)	0.59 (0.59-0.60)	0.59 (0.58-0.60)	0.58 (0.59-0.60)
LACE (95% CI)	0.58 (0.58–0.59)	0.58 (0.58-0.60)	0.58 (0.57–0.59)

LaCE (95% CI)	0.60 (0.59–0.60)	0.61 (0.60-0.62)	0.60 (0.59-0.61)
For outcome of 30 day death after index admission			
Charlson (95% CI)	0.44 (0.43-0.46)	0.49 (0.46-0.52)	0.50 (0.48-0.53)
Krumholz (95% CI)	0.68 (0.67-0.69)	0.64 (0.62-0.66)	0.66(0.64-0.68)
Keenan (95% CI)	0.69 (0.68-0.70)	0.68 (0.66-0.70)	0.66 (0.65-0.70)
LACE (95% CI)	0.55 (0.54-0.56)	0.55 (0.54-0.56)	0.56 (0.54, 0.57)
LaCE (95% CI)	0.67 (0.66-0.69)	0.64 (0.62-0.66)	0.66 (0.64-0.68)

Table 2.4. Net Reclassification Index for various models for prediction of primary outcome (death or readmission within 30 days of discharge)

Models	Charlson	LACE	LaCE	Krumholtz	Keenan
Charlson	0	12.6 (10.5, 14.7)	20.5 (18.4-22.5)	0.06% (0.1%, 0.03%)	2.6% (0.5% - 4.6%)
LACE		0	4.5 (2.4-6.5)	-0.05 (-2.6-1.5)	-15.0 (-17.1, -12.9)
LaCE			0	-1.8 (-3.8-0.2)	-19.1 (-21.2, -17.1)
Krumholtz				0	1.0 (-2.1, 2.1)
Keenan					0

Figure 2.1. Gini Score Plot based on a random forest model



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Chapter 3

Outcomes in teaching versus nonteaching general internal medicine services: systematic review and meta-analysis[2]

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[2] *A version of this chapter has been submitted for publication.*

All health care systems train their future practitioners in clinical settings. As a result, patients may be cared for on teaching services (comprising trainee physicians with oversight from teaching faculty with varying degrees of experience) or on non-teaching services (clinicians with varying degrees of experience but without trainee involvement). While most studies in fields outside of general internal medicine suggest that patient care is generally of similar quality when delivered by trainee physicians as by faculty(1), it is unclear whether outcomes are better or worse for patients cared for on teaching compared to non-teaching inpatient clinical services. This is an important question to answer since some studies (2-4) suggest that care in teaching hospitals is more costly than that provided in non-teaching ones, although other studies have not confirmed this.(5) Thus, we designed this systematic review to address the question of whether patient-relevant outcomes differed for general internal medicine patients cared for on teaching or non-teaching services.

Although earlier studies(2, 3, 6-9) suggested that quality of care was better in teaching hospitals, a recent systematic review on this topic was unable to reach a firm conclusion due to excessive heterogeneity.(10) As we hypothesized that much of this heterogeneity may have resulted from trying to combine studies done in different patient populations and comparing outcomes between different institutions or over different time frames, we designed this review to focus specifically on general internal medicine inpatient wards and restricted the review to only those studies comparing outcomes in patients admitted to teaching services or non-teaching services within the same hospital . We focused on general internal medicine wards as the majority of internal medicine training occurs in this setting.(11) The outcomes we examined were those highlighted in the Affordable Care Act (12) and are consistent with current recommendations from the Centers for Medicare and Medicaid Services(13): in-hospital mortality, 30 day readmission rates, and lengths of stay.

METHODS

Search Strategy

In collaboration with a research librarian, we conducted a systematic search of Medline (from 1950), EMBASE (from 1980) and the Cochrane Library in May, 2012. We used the following MeSH terms and keywords: (Teaching OR academic OR university OR medical school*) AND (hospital OR center) AND (outcome* OR readmission* OR hospitalization* OR length of stay OR mortalit*). We also reviewed reference lists from the included studies and review articles to identify further studies.

Study selection and data abstraction

The literature search was screened independently by two reviewers (AA and RP). Studies were included if they met all of the following criteria: 1) patients aged 18 years or older admitted to a general internal medical service with outcomes for those patients treated on teaching services identifiable; 2) randomized controlled trials or observational studies with contemporaneous control groups; 3) outcomes included at least one of in-hospital mortality, 30 day readmission rates and length of stay (LOS). Studies were excluded if they did not contain original data (i.e. editorials, opinion articles, or narrative review articles) or were not peer reviewed (such as meeting abstracts), if they were not published in English or were published before 1970, or if they included surgical patients or patients cared for in critical care settings.

Outcome data were extracted from all included articles and quality assessed (using the Cochrane Effective Practice and Organisation of Care (EPOC) risk of bias tool)(14) in duplicate and independently by AA and RP, with differences of opinion adjudicated by FAM. This review was prepared in compliance with PRISMA reporting guidelines(15).

Definition of exposure groups

We compared patients admitted to a teaching service versus those admitted to a non-teaching service. The definition of a teaching service included a team comprised of an attending physician (academic university-based or community-based physician) and postgraduate or undergraduate trainees. The attending physician could comprise of either a general internist or a subspecialist if his/her role was as the attending physician on a general medicine team where his/her roles and responsibilities included providing care similar to a general internist and the teaching of trainees in principles and practices of general internal medicine. .A non-teaching service comprised a treating physician (academic university-based or community-based physician) with or without physician assistants but did not include postgraduate or undergraduate trainees.

Data analysis:

We used Review Manager (Version 5.1. Copenhagen: The Nordic Cochrane Centre, The Cochrane Collaboration, 2011) to calculate Mantel-Haenszel odds ratios (OR) and 95% confidence intervals for each outcome using random effects models. We explored between study heterogeneity using the I-squared statistic, and considered values less than 25% to be low, 25 to 50% modest, and greater than 50% to represent substantial heterogeneity(16), although we did not pre-specify a degree of heterogeneity that would preclude pooling of data. We pre-specified two sensitivity analyses to better understand heterogeneity by stratifying studies according to (1) whether or not they provided estimates of effect adjusted for baseline characteristics and (2) if the studies were of higher quality (score of 3 or more on the Cochrane Effective Practice and Organisation of Care [EPOC] risk of bias tool(14)).

RESULTS

Studies included in the systematic review:

Of the 8137 citations identified in our electronic and hand searches, 15(17-31) studies fulfilled our eligibility criteria (Figure 1) - inter-rater kappa for study eligibility was 0.96. One study was a randomized controlled trial (contributing 0.8% of the outcome data in this review) and 14 studies were cohort studies (99.2% of outcome data) – all studies had contemporaneous controls. Data in these studies came from 108 570 patients from 1987 to 2011, and their key characteristics are outlined in Appendix 1. Thirteen studies included patients with a variety of medical diagnoses while one(24) study focused on patients admitted for chest pain and one(30) study focused on pneumonia patients. Four studies reported minor involvement of postgraduate or undergraduate trainees on their non-teaching services: one(20) reported that 5% of the patients on the non-teaching service were cared for by postgraduate trainees, one(23) had the occasional 3rd or 4th year medical student on rotation (but no interns or residents) and the other two (24,28) reported overnight or weekend coverage of varying degrees by postgraduate trainees.

Qualitative data synthesis (e-appendix Table 1):

The quality of the included studies was generally low to moderate and the majority of studies scored poorly on the EPOC risk of bias tool (e-appendix Table 1): median score was 2 with interquartile range of 1 to 3 out of a possible maximum score of 9. In particular, while all had contemporaneous controls, the 14 cohort studies were at high risk of allocation bias due to the non-random nature by which patients were assigned to the teaching or non-teaching services: based on pre-assigned patient caseload caps(22, 23, 25, 27), time of day(29), alternating sequence(18), the attending physician call schedule(26, 31), patient insurance status(20) , at the discretion of the ED physician(30), or patient preference(30). This contributed to moderate differences between the teaching and non-teaching services in prognostically important baseline characteristics (e-Appendix table 1) such as age(19-21, 25, 28, 30), sex(18, 20-24, 31), type of insurance(19, 21, 26, 27, 30), ethnicity(24), and number of comorbidities(25); based on these characteristics, patients admitted to non-teaching services had in general somewhat better prognoses. Studies of high quality were distinguishable from the lower quality studies mostly due to baseline characteristics being similar between the teaching and non-teaching patients. Fourteen of the 15 studies were conducted at single institutions with teaching and non-teaching services in the same building.

All of these studies reported blinded outcomes ascertainment. However, 11 of the 15 studies used administrative data exclusively, 3 (17, 20, 30) used a combination of administrative and primary data, and one study did not state how data was obtained(24).

The one RCT (17) in this field was of moderate quality scoring 3 out of 5 on the Jadad scale since blinding was not possible(32). It used both administrative and medical records to identify clinical and financial outcomes from time of admission up until 8 months after the close of the study.

Quantitative data synthesis:

In-patient mortality (Figure):

Of the 13 studies (108 015 patients) which reported this outcome, 3 reported statistically significant results: one(21) demonstrated lower mortality for patients admitted to a teaching service while two(22, 25) reported higher mortality rates. However, all 3 of these studies were of low quality, and the only RCT in this field 17 did not detect any impact of teaching versus non-teaching service on inpatient mortality. The pooled estimate from all 13 studies (Fig) revealed no difference for in-patient mortality between patients admitted to a teaching or non-teaching service (2.5% vs. 2.8%, OR 1.07, 95% CI 0.87 to 1.32, I-squared 82%). Results were consistent in the 4 risk-adjusted studies (19, 23, 28, 29) (53 360 patients, aOR 0.91, 0.76 to 1.08, I-squared 0%) and in the 7 higher quality studies (30 544 patients, OR 0.94, 0.73 to 1.21, I-squared 44%)(17, 18, 23, 27-29, 31).

30-day readmissions (Figure):

Of the 11 studies (106 021 patients) which reported this outcome, 4 reported statistically significant results: 3(19, 25, 27) reported a higher readmission rate for patients discharged from teaching services (all of which reported that patients on the teaching service were younger and more likely to be on Medicaid) and one (which was the only one of the 4 statistically significant studies meeting the EPOC definition for high quality)(22) reported a lower readmission rate. The only randomized trial in this field(17), which was not included in our pooled estimates since they evaluated 15 day readmission rate rather than 30 day, did not find any difference between the teaching and non-teaching services (6.8% vs. 7.8%, p=0.67). The pooled estimate from the 11 observational studies (Fig) revealed no difference in the unadjusted 30 day readmission rate for teaching versus non-teaching services (15.1% vs.13.1%, OR 1.05 95% CI: 0.93 to 1.18), but there was substantial heterogeneity (I-squared 89%). Pooling the risk-adjusted estimates from the 4 studies(19, 23, 28, 29) revealed no statistically significant difference between the teaching and non-teaching services (34 320 patients, OR 1.12, 95% CI 0.94 to 1.32, I-squared 72%).

Length of hospital stay (Figure):

Of the 15 studies that reported this outcome, 11 (82 352 patients) reported data which could be pooled. Of the 3 studies not meta-analyzable because of incomplete data even after contact with primary study authors,(19-21, 24) all reported shorter LOS on the teaching services: 1.36 days (19), 0.84 days (20), and 0.38 days (24). The other study which we did not meta-analyze(31) excluded 11% of their patients as their LOS were “outliers”.

While the pooled estimate from the 11 pooled studies (Fig) revealed a statistically longer LOS for patients admitted to the teaching service compared to the non-teaching service (mean difference: 0.40 days, 95% CI 0.04 to 0.77), there was substantial heterogeneity in this result (I-squared 95%). Three studies (21, 27, 29) reported statistically significantly shorter LOS for those cared for on the teaching service, and five studies(17, 18, 22, 25, 26) - including the only RCT on this topic - reported statistically significantly longer LOS. In two of the studies reporting longer LOS for patients cared for on teaching services, patients had more comorbidities (25) and diagnosis related groups (DRGs) on the teaching service(18) and the apparent difference between the teaching and non-teaching LOS disappeared after multivariate adjustment. Indeed, pooling the data from those 4 risk-adjusted studies (18, 23, 28, 29) revealed no difference in mean LOS (22 607 patients, mean difference: -0.09 days, 95% CI -0.24 to +0.06, I-squared 52%). When we restricted our analysis of the unadjusted LOS data to only those studies of better quality,(17, 18, 23, 24, 27-29), there was no difference in mean LOS between the teaching and non-teaching services (6 studies, 29 073 patients, mean difference: -0.05 days, 95% CI -0.37 to +0.28). Restricting the analysis to those studies in which patients in both arms were cared for on the same nursing units(17, 23, 27, 29) also revealed no difference in LOS between teaching and non-teaching services (4 studies, 18 336 patients, mean difference: -0.15 days, 95%CI -0.65 to +0.35 days, I-squared: 86%).

DISCUSSION:

This systematic review of 15 studies with contemporaneous controls revealed no substantive differences for in-patient mortality, 30 day readmission rates, or length of hospital stay for general internal medicine patients admitted to teaching or non-teaching services. Although there was substantial unexplained heterogeneity between studies, findings were largely consistent in analyses restricted to higher quality studies or studies that adjusted for baseline imbalances in prognostically important characteristics between groups.

We are not aware of any similar reviews that have focused on general internal medicine patients. A recent systematic review (10) of 93 studies (0 of which were included in our systematic review) in medical and surgical patients reported no mortality difference between patients managed on teaching versus non-teaching services but substantial heterogeneity was present in that analysis as well (I-squared 72%). In a recent analysis from the CRUSADE Initiative, Patel and colleagues reported similar findings to ours but for patients with acute coronary syndrome only (33).

There was substantial heterogeneity in our analyses. Some of the heterogeneity can be explained by differences in baseline characteristics between the teaching and non-teaching cohorts as well as differences in the care units where teaching service patients were located compared with non-teaching service patients. When the analysis was restricted to higher quality studies or to studies where cohorts were located on the same nursing units, heterogeneity was reduced. Heterogeneity was reduced in those studies that adjusted for age(34), Charlson co-morbidity index(35), or number of co-morbidities(34, 36), suggesting that these factors are major drivers of LOS and inpatient mortality in the studies we identified. As we included any study that reported outcomes of patients on a general internal medicine service, the types of diseases that were treated varied considerably, undoubtedly contributing to the heterogeneity we observed since there was substantial residual heterogeneity even when we subgrouped studies by mean age, gender, Case Mix Index, mean Charlson Comorbidity Index scores, sample size, year of publication, or community vs. tertiary 14hospital.

Hospital costs are an increasingly important issue as healthcare expenditures continue to rise. Teaching hospitals care for more severely ill patients, offer more specialized units, services and technologies, and healthcare personnel (including sub-specialists).(7) Some studies have suggested that in-hospital patient costs may be higher in teaching hospitals (2-4), but of the 10 studies included in our review which addressed this issue (18-21, 23, 24, 28-31) 4(19-21, 30) reported lower hospital costs for patients admitted to a teaching service and 2 reported no significant differences (23, 29) compared to non-teaching services. While not a primary goal of our systematic review, it is clear that the evidence is not definitive on this point and more primary research is required. In a broader sense, the potential impact of teaching vs. non-teaching services on hospital-level outcomes that may induce financial penalties to institutions under the Affordable Care Act (such as 30 day readmission rates) is also an important factor to consider when evaluating the costs of teaching vs. non-teaching general internal medicine services and this was the primary goal of our systematic review.

Our systematic review has some limitations. We only identified one relatively small RCT with over 99% of our data being drawn from observational studies. Although we only included observational studies with contemporaneous control groups in our review (a study design endorsed by the Cochrane Effective Practice and Organisation of Care group for topics such as this)(14), residual confounding and selection bias remain threats to the validity of our observations. Only half of the studies reported baseline characteristics that were similar between the teaching and non-teaching groups. Most studies used administrative data, which precludes fully adjusting for severity of disease or functional status.(37, 38) Four studies reported minor involvement of post-graduate or undergraduate trainees on the non-teaching services which could have mitigated the differences in outcomes between the two groups. Fourteen of the 15 studies were single institution studies which are then subject to potential contamination as the physicians on different services can discuss cases and patients in both groups share the same multidisciplinary services. Moreover, one study (n=2189 patients) rotated their hospitalists between the teaching and non-teaching services (23). Finally, we were unable to adjust for different levels of inpatient expertise among the attending physicians which could have varied significantly between and within studies. This could have potentially resulted in less pronounced outcome differences between the teaching and non-teaching groups.

In conclusion, despite including data from over 100,000 patients in our review we could not find any evidence for substantive differences in outcomes for general internal medicine patients according to whether they were admitted to a teaching or a non-teaching service. We speculate that penetration of health information technologies, performance measurement and incentives or penalties, patient volumes and case-mix, and unit staffing ratios are far more important to the delivery of high quality care and achievement of good outcomes than whether teaching faculty and trainees are present or not (39-41). Given that teaching hospitals play an important role in training future generations of providers(39), and those that also participate in research deliver better quality of care and achieve better outcomes than those which do not,(42) our results should lessen concerns hospital administrators in teaching hospitals may have about maintaining or introducing general internal medicine teaching units in light of moves to financially penalize hospitals that have higher than predicted LOS or readmission rates.

Figure 3.1. Flow diagram of screened, included, and excluded articles.

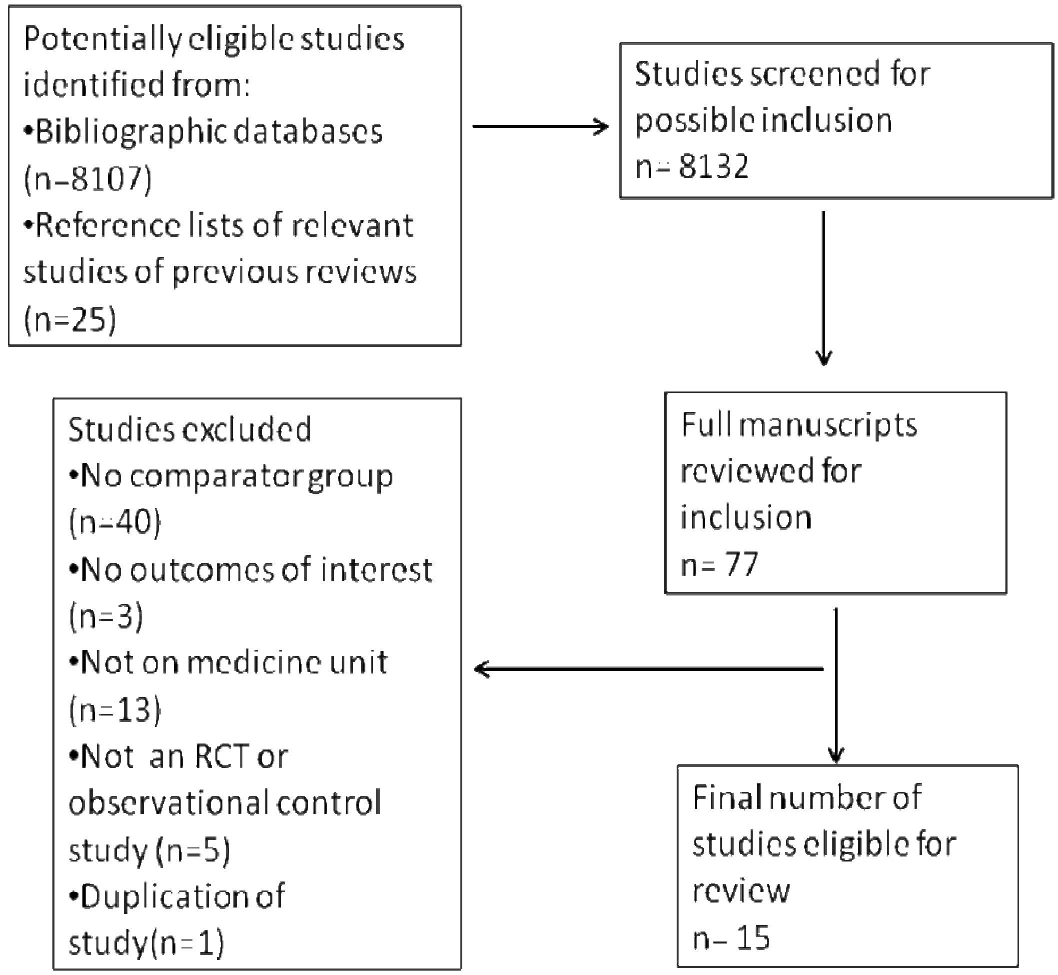


Table 3.1. Study characteristics

Study	Location	Time Period	Number of patients in study	Data source	Teaching service*	Non-teaching service	Shared nursing units between teaching and non-teach-ing services	Most common medical diagnoses	Outcomes
randomized controlled studies									
Simmer (17)	Detroit, Michigan, U.S.	Oct 1987-Sept 1998	883	Primary and Administr-ative	attending physician(academic internists), post-graduate trainees, undergraduate trainees	2 senior staff physicians(academic internists), physician assistant, medical assistant	yes	not listed	Length of stay, in-patient mortality, 15 day readmission rate
cohort studies									
Dynan (18)	Cincinnati, Ohio, U.S.	June 2006 - July 2007	5543	Administr-ative, physician interviews	teaching faculty(academic internist), post-graduate trainees, undergraduate trainees +/- clinical pharmacist or pharmacy resident	hospitalist and nurse practitioner	unknown	not listed	Length of stay, 30 day readmission rate

Everett (19)	Florida, U.S.	October 2000-June 2004	22792	Administr-ative	academic internists with post-graduate trainees	community general internists or private hospitalists	unknown	all patient refined diagnosis related group: cardiovascular disorders, respiratory disorders, digestive diseases	Length of stay, in-patient mortality, 30 day readmission rate
Hackner (20)	Los Angeles, California, U.S.	July 1996-June 1997	1637	Primary + Administr-ative	Hospitalist attending physician and post-graduate trainees	private provider with staff privileges (majority community physicians, no general practitioner or family physicians)	unknown	not listed	Length of stay, in-patient mortality, 30 day readmission rate
Halasyamani (21)	Southeast Michigan	July 2001-June 2002	10595	Administr-ative	academic hospitalist, post-graduate trainees and undergraduate trainees.	community general internist or private hospitalists and house physician	yes	stroke, pneumonia, arrhythmia, asthma/COPD	Length of stay, in-patient mortality, 30 day readmission rate
Horwitz (22)	Connecticut, U.S.	July 2002-June 2003†, July 2003 –June 2004‡	20924	Administr-ative	physician with post-graduate and under-graduate trainees	hospitalist and physician assistant(s)	unknown	coronary artery disease, dysrhythmia, congestive heart failure,	Length of stay, in-patient mortality, 30 day read-mission rate

								chest pain	
Khaliq (23)	U.S.	February-October 2002	2189	Administr-ative	attending physician (hospitalist or clinic-based internist) and post-graduate trainees	hospitalist or clinic-based internist (occasional undergraduate trainee)	yes	community-acquired pneumonia, gastrointestinal bleed, congestive heart failure, metabolic disorders	Length of stay, in-patient mortality, 30 day readmission rate
Myers (24)	Philadelphia, Pennsylvania, U.S.	July 2002 - June 2003	318	not stated	hospitalist and post-graduate and undergraduate trainees	hospitalist and nurse practitioners	unknown	chest pain	Length of stay, 30 day readmission rate
O'Connor 2009 (25)	Rochester, New York, U.S.	January 2005- June 2005	6907	Administr-ative	attending physician (academic hospitalist , community-based primary care provider, or subspecialty attending) post-graduate and under-graduate trainees	Attending physician (academic hospitalists, community primary care internists, and/or university-based subspecialty attendings), nurse practitioner and physician assistants	unknown	pneumonia, congestive heart failure, respiratory failure, chest pain, COPD exacer-bation	Length of stay, in-patient mortality, 30 day readmission rate
O'Connor 2011 (26)	Rochester, New York, U.S.	2007-2008§, 2008-2009‖	7532	Administr-ative	attending physician (academic hospitalist , community-	Attending physician (academic hospitalists, community	unknown	not listed	Length of stay, in-patient mortality, 30 day

					based primary care provider, or subspecialty attending) post-graduate and undergraduate trainees	primary care internists, and/or university-based subspecialty attendings), nurse practitioner and physician assistants			readmission rate
Palacio (27)	Jacksonville, Florida, U.S.	Nov-ember 2006 - April 2007		Administr-ative	internal medicine service (clinic-based internist) and post-graduate trainees	Hospitalist service (internist, family physician, or physician extender)	yes	not listed	Length of stay, in-patient mortality, 30 day readmission rate
Roy (28)	North-eastern U.S.	July 2005-June 2006 (week-ends excluded as non-teaching service did not admit on week-ends)	5194	Administr-ative	Attending physician (hospitalist, primary care physician, or medical subspecialist) and postgraduate and under-graduate trainees	Hospitalist and Physician Assistants (moonlighting post-graduate trainee on weekend)	unknown	chest pain, esophagitis /gastroenteritis/miscellaneous digestive disorders, heart failure and shock	Length of stay, in-patient mortality, 30 day readmission rate

Singh (29)	Milwaukee, Wisconsin, U.S.	January 2005-December 2006		Administr-ative	hospitalist/non-hospitalist general internist or specialist (rarely) and post-graduate trainees	hospitalist-physician assistant teams	yes	pneumonia, congestive heart failure, sickle cell anemia, non-specific chest pain	Length of stay, in-patient mortality, 30 day readmission rate
Stein (30)	Providence, Rhode Island, U.S.	1995	237	Primary + Administr-ative	faculty attending physician or community-based internist and trainees	community-based internist	unknown	pneumonia	Length of stay, 30 day readmission rate
Van Rhee (31)	Midwest, U.S.	January 1994-June 1995	1111	Administr-ative	attending physician (general internal medicine physicians, cardiologists, gastroenterologists, and neurologists) and post-graduate trainees	attending physician (general internal medicine physicians, cardiologists, gastroenterologists, and neurologists and physician assistant	yes	CVA/stroke, pneumonia, acute MI, CHF, GI hemo-rrhage	Length of stay, inpatient mortality rate

*Studies where subspecialists and neurologists were acting as the attending physician on a general internal medicine service were included.

†Horwitz 2007a, ‡Horwitz 2007b, §O'Connor 2011a, ||O'Connor 2011b refers to the comparison groups for the meta-analysis (both studies included teaching vs. non-teaching comparisons in two different time periods).

E-appendix.

eTable 3.1. Risk of Bias for Included Studies*

Study Author	Type of Study	Allocation sequence random?	Allocation con-cealed?	Baseline out-comes similar?	Baseline charact-eristics similar?	Plan for Missing Data/Incom-plete Measure-ment of Primary Outcome (Outreach to Find Other Site Re-admissions)?	Out-comes Assessed Blind to Inter-vention?	No conta-mina-tion?	Free of Selective Outcome Reporting Risk?	No Other Bias?(including whether study was from single institution)	EPOC Group Risk of Bias Criteria Total (9 Max-imum)
Randomized controlled studies											
Simmer	RCT	yes	yes	unclear	yes	unclear	yes	unclear	yes	no	5
cohort studies											
Dynan	cohort	no	no	unclear	yes	unclear	yes	unclear	yes	no	3
Everett	retro cohort	no	no	unclear	no	unclear	yes	unclear	yes	no	2
Hackner	retro cohort	no	no	unclear	no	unclear	yes	unclear	yes	no	2
Halasyamani	retro cohort	no	no	unclear	no	unclear	yes	unclear	yes	no	2
Horwitz	retro cohort	no	no	unclear	no	unclear	yes	unclear	yes	no	2
Khaliq	cohort	no	no	unclear	yes	unclear	yes	unclear	yes	no	3
Myers	cohort	no	no	unclear	yes	unclear	yes	unclear	yes	no	3
O'Connor 2009	retro cohort	no	no	unclear	no	unclear	yes	unclear	yes	no	2
O'Connor 2011	cohort	no	no	unclear	no	unclear	yes	unclear	yes	no	2

Palacio	retro cohort	unclear	no	unclear	yes	unclear	yes	unclear	yes	no	3
Roy	retro cohort	no	no	unclear	yes	unclear	yes	unclear	yes	no	3
Singh	retro cohort	no	no	unclear	yes	yes	yes	unclear	yes	no	4
Stein	retro cohort	no	no	unclear	no	unclear	yes	unclear	yes	no	2
Van Rhee	retro cohort	no	no	unclear	yes	no	yes	unclear	yes	no	3

*all studies from a single institution except O'Connor 2009 which was comprised of data from two affiliated hospitals (both of which had teaching and non-teaching services)

RCT: randomized control study

eTable 3.2. Differences in baseline characteristics for included studies

Study	Age		Gender (male)		Ethnicity		Insurance status		Admissions through Emergency department		Charlson score		DRG case-mix index	
	Teach-ing	Non-teaching	Teach-ing	Non-Teach-ing	Teach-ing	Non-Teach-ing	Teach-ing	Non-Teach-ing	Teach-ing	Non-Teach-ing	Teach-ing	Non-teach-ing	Teach-ing	non-teach-ing
RCT														
Simmer	61.7	61.2	51.4%	56.4 %	24.1 % white, 72.2 % black	21.8 % white, 75.8 % black	NR	NR	NR	NR	NR	NR	1.09	1.18
cohort studies														
Dynan	53.1	53.6	51.9%	47.3 %	43.0 % white, 51.8 % black	43.2 % white, 52.3 % black	39.5% Medi-care, 29.1% Medicaid	36.5 % Medi-care, 29.4 % Medicaid	85.1%	89.0%	NR	NR	NR	NR
Everett	58.6	64.0	44.3%	42.1 %	59.4 % white, 34.1 % black	59.3 % white, 24.8 % black	58.8% Medi-care, 7.7% Medi-caid	67.9 % Medi-care, 6.5% Medi-caid	NR	NR	NR	NR	NR	NR
Hackner	52.8	56.4	41.0%	50.2 %	63.1 % white, 28.3 % black	62.2 % white, 21.6 % black	NR	NR	NR	NR	NR	NR	NR	NR

Halasyamani	62.6	68.2	46.4%	42.1%	NR	NR	53.6% Medicare, 3.0% Medicaid	65.0% Medicare, 11.8% Medicaid	86.6%	75.2%	NR	NR	NR	NR
Horwitz a*	62.9	62.5	50.9%	47.0%	70.8% white, 19.6% black	67.7% white, 22.2% black	52.8% Medicare, 12.4% Medicaid	53.3% Medicare, 13.3% Medicaid	65.8%	87.0%	Deyo score 0: 52.7%, 1:25.0%, 2:12.4%, ≥3: 9.8%	Deyo score 0: 55.1%, 1:24.6%, 2:10.7%, ≥3: 9.5%	NR	NR
Horwitz b†	62.7	62.9	49.8%	43.6%	69.5% white, 20.4% black	67.8% white, 22.2% black	53.7% Medicare, 12.9% Medicaid	53.9% Medicare, 12.6% Medicaid	70.4%	91.0%	Deyo score 0: 49.6%, 1:27.0%, 2:13.3%, ≥3: 10.1%	Deyo score 0: 50.6%, 1:26.9%, 2:12.7%, ≥3: 9.8%	NR	NR
Khaliq	67.1	67.5	50.0%	46.4%	NR	NR	66.9% Medicare, 4.7% Medicaid	67.8% Medicare, 5.6% Medicaid	NR	NR	6.7	6.7	NR	NR
Myers	50.1	50.3	36.6%	42.5%	30.2% white, 65.3% black	15.9% white, 77.9% black	NR	NR	NR	NR	NR	NR	NR	NR

O'Connor 2009	64.0 (49.0-80.0) ¶	69.0 (51.0-82.0) ¶	50.4%	44.2 %	72.1 % White, 23.2 % black	74.3 % White, 20.3 % black	43.1% Medi-care, 13.0% Medi-caid	44.4 % Medi-care, 9.2% Medi-caid	NR	NR	0: 23.7%, 1-2: 24.3%, 3-5: 27.3%, >5: 24.7 % 9.0 (6.0-12.0) #	0: 29.8 %, 1-2: 28.0 %, 3-5 :23.5 %, >5: 18.8 % 8.0 (6.0-11.0) #	NR	NR
O'Connor 2011a‡	61 (47-76)¶	63 (48-78)¶	50.6%	49.6 %	NR	NR	39.0% Medi-care, 12.6% Medi-caid	43.0 % Medi-care, 11.7 % Medi-caid	NR	NR	4.0(1.0-7.0) #	3.0(1.0-7.0) #	NR	NR
O'Connor 2011b§	61 (46-77)¶	63 (48-78)¶	53.1%	48.8 %	NR	NR	41.2% Medi-care, 13.0% Medi-caid	44.4 % Medi-care, 10.5 % Medi-caid	NR	NR	3.0(1.0-6.0) #	3.0(1.0-6.0) #	NR	NR
Palacio	56.7	58.2	48.8%	45.6 %	38.2 % white, 58.4 % black	41.4 % white, 55.2 % black	43.7% Medi-care, 15.8% Medicaid	48.5 % Medi-care, 13.5 % Medicaid	NR	NR	*1.14 ± 1.02*	*1.04 ± 0.94*	NR	NR

Roy	age 18-44: 18.2%, 45-64: 31.9%, 65+: 49.9%	age 18-44: 19.1%, 45-64: 35.5%, 65+: 45.5%	40.0%	42.3%	59.3% white, 23.5% black	57.3% white, 24.0% black	43.8% Medicare, 11.7% Medicaid	41.9% Medicare, 14.4% Medicaid	NR	NR	0: 24.9%, 1: 21.1%, 2: 16.5%, ≥3: 37.6%	0: 27.2%, 1: 22.6%, 2: 16.2%, ≥3: 34.0%	1.2	1.1
Singh	57.0	56.8	44.9%	45.9%	58.9% white, 36.7% black	59.1% white, 36.5% black	47.8% Medicare, 33.0% Medicaid/others	46.8% Medicare, 32.9% Medicaid/others	80.7%	76.6%	*0.38*	*0.39*	NR	NR
Stein	63	75	NR	NR	NR	NR	56.4% Medicare, Medicaid NR	74% Medicare, Medicaid NR	NR	NR	NR	NR	NR	NR
Van Rhee"	<65: 25.3%, 65-79: 41.8% , ≥ 80: 32.9%	<65: 29.8%, 65-79: 40.1%, ≥80: 30.1	49.6%	56.7%	NR	NR	76.2% Medicare, Medicaid NR	72.9% Medicare, Medicaid NR	82.7%	83.1%	NR	NR	NR	NR

*2002-2003 cohort † 2003-2004 cohort
‡2007-2008 cohort §2008-2009 cohort
" demographics are based on 923 patients as outliers (3 standard deviations from mean) were removed from analysis by authors
¶median age (interquartile range)
median number of co-morbidities (interquartile range)
italics: median number of co-morbidities
RCT+ randomized controlled trial, NR= not reported

Figure 3.2. Unadjusted in-patient mortality on Teaching vs. Non-Teaching General Internal Medicine Services

	teaching service		non-teaching service			Odds Ratio
Study or Subgroup	Events	Total	Events	Total	Weight	M-H, Random, 95% CI
Simmer 1991	36	437	23	446	5.6%	1.65 [0.96, 2.84]
Dynan 2009	25	3160	21	2383	5.2%	0.90 [0.50, 1.61]
Everett 2007	120	5691	388	17101	8.3%	0.93 [0.75, 1.14]
Hackner 2001	11	477	42	1160	4.6%	0.63 [0.32, 1.23]
Halasyamani 2005	107	4118	226	6477	8.1%	0.74 [0.58, 0.93]
Khaliq 2007	61	1637	25	552	6.1%	0.82 [0.51, 1.31]
O'Connor 2009	162	1976	221	4931	8.3%	1.90 [1.54, 2.35]
Palacio 2009	38	2244	63	3699	6.7%	0.99 [0.66, 1.49]
Roy 2008	50	4202	7	992	3.8%	1.69 [0.77, 3.75]
Singh 2011	95	7510	39	2171	6.9%	0.70 [0.48, 1.02]
Van Rhee 2002	29	599	36	512	5.9%	0.67 [0.41, 1.11]
Horwitz 2007a	170	7018	40	2954	7.2%	1.81 [1.28, 2.56]
Horwitz 2007b	147	7242	41	3710	7.2%	1.85 [1.31, 2.63]
O'Connor 2011a	116	2501	233	4583	8.1%	0.91 [0.72, 1.14]
O'Connor 2011b	123	2916	178	4616	8.1%	1.10 [0.87, 1.39]
Total (95% CI)		**51728**		**56287**	**100.0%**	**1.07 [0.87, 1.32]**
Total events	1290		1583			

Heterogeneity: Tau² = 0.12; Chi² = 76.66, df = 14 (P < 0.00001); I² = 82%
Test for overall effect: Z = 0.66 (P = 0.51)

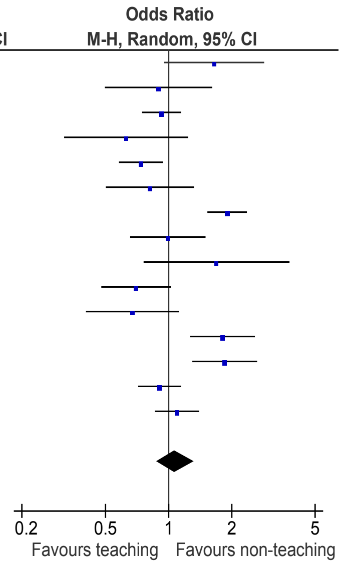


Figure 3.3. Unadjusted 30 day readmission rate on Teaching vs. Non-teaching General Internal Medicine Services.

	teaching service		non-teaching service			Odds Ratio
Study or Subgroup	**Events**	**Total**	**Events**	**Total**	**Weight**	**M-H, Random, 95% CI**
Dynan 2009	423	3160	310	2383	7.8%	1.03 [0.88, 1.21]
Everett 2007	558	5691	1248	17101	8.5%	1.38 [1.24, 1.53]
Hackner 2001	88	477	219	1160	6.1%	0.97 [0.74, 1.28]
Halasyamani 2005	593	4118	891	6477	8.4%	1.05 [0.94, 1.18]
Horwitz 2007a	1152	7018	563	2954	8.4%	0.83 [0.75, 0.93]
Horwitz 2007b	1323	7242	848	3710	8.5%	0.75 [0.68, 0.83]
Khaliq 2007	202	1637	57	552	5.6%	1.22 [0.90, 1.67]
O'Connor 2009	268	1976	541	4931	7.8%	1.27 [1.09, 1.49]
O'Connor 2011a	450	2501	885	4583	8.2%	0.92 [0.81, 1.04]
O'Connor 2011b	499	2916	822	4616	8.3%	0.95 [0.84, 1.08]
Palacio 2009	316	2244	385	3699	7.8%	1.41 [1.20, 1.65]
Roy 2008	340	4202	79	992	6.4%	1.02 [0.79, 1.31]
Singh 2011	1436	7510	383	2171	8.2%	1.10 [0.97, 1.25]
Total (95% CI)		**50692**		**55329**	**100.0%**	**1.05 [0.93, 1.18]**
Total events	7648		7231			

Heterogeneity: Tau² = 0.04; Chi² = 112.78, df = 12 (P < 0.00001); I² = 89%
Test for overall effect: Z = 0.80 (P = 0.43)

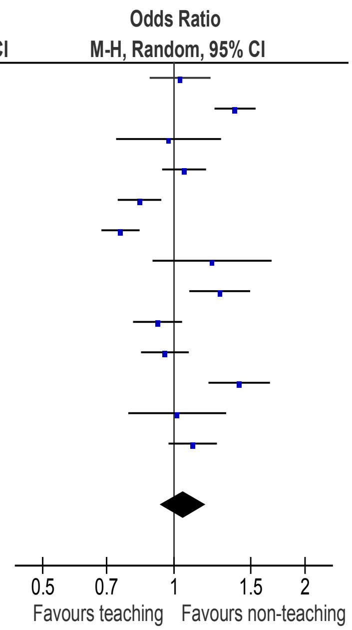
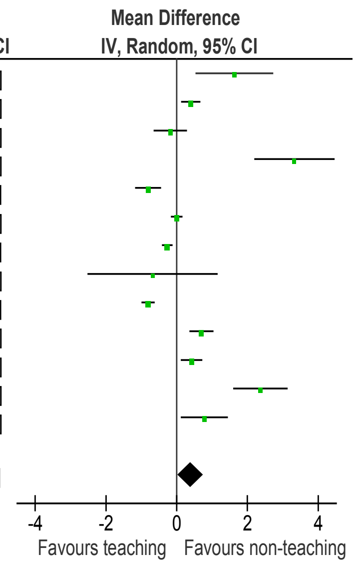


Figure 3.4. Unadjusted length of stay on Teaching vs. Non-teaching General Internal Medicine Services.

Study or Subgroup	teaching service Mean	SD	Total	non-teaching service Mean	SD	Total	Weight	Mean Difference IV, Random, 95% CI
Simmer 1991	9.21	8.33	437	7.58	7.99	446	5.3%	1.63 [0.55, 2.71]
Dynan 2009	4.596	5.063	3160	4.2	4.634	2383	9.1%	0.40 [0.14, 0.65]
Khaliq 2007	4.92	4.673	1637	5.1	4.673	552	8.4%	-0.18 [-0.63, 0.27]
O'Connor 2009	10.16	24.034	1976	6.835	12.625	4931	5.1%	3.33 [2.21, 4.44]
Palacio 2009	4.14	5.95	2244	4.95	7.77	3699	8.8%	-0.81 [-1.16, -0.46]
Roy 2008	2.6	2.1421	4202	2.6026	2.1421	992	9.4%	-0.00 [-0.15, 0.15]
Singh 2011	2.99	2.7007	7150	3.26	2.7071	2171	9.5%	-0.27 [-0.40, -0.14]
Stein 1998	5.8148	6.0858	162	6.5	6.9	75	2.9%	-0.69 [-2.51, 1.14]
Halasyamani 2005	3.99	4.27	4118	4.7957	4.3004	6477	9.4%	-0.81 [-0.97, -0.64]
Horwitz 2007a	5.21	9.3	7018	4.51	6.6	2954	8.9%	0.70 [0.38, 1.02]
Horwitz 2007b	5.04	9.2	7242	4.62	5.9	3710	9.0%	0.42 [0.14, 0.70]
O'Connor 2011a	9.934	15.114	2501	7.569	15.799	4583	6.9%	2.36 [1.62, 3.11]
O'Connor 2011b	8.398	14.39	2916	7.617	13.256	4616	7.4%	0.78 [0.13, 1.43]
Total (95% CI)			**44763**			**37589**	**100.0%**	**0.40 [0.04, 0.77]**

Heterogeneity: Tau² = 0.37; Chi² = 238.07, df = 12 (P < 0.00001); I² = 95%
Test for overall effect: Z = 2.15 (P = 0.03)



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Chapter 4

Teaching hospitals and weekday discharges are associated with better outcomes in heart failure[3]

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[3] *A version of this chapter has been submitted for publication.*

Hospitals typically reduce both staffing levels and the availability of diagnostic and treatment services on weekends, which may impact patient care(1-5). Notably, in-hospital mortality is higher in patients admitted on weekends for several medical conditions such as heart failure (HF), pneumonia, and COPD exacerbations (3, 4, 6-12). This phenomenon has been termed the “weekend effect”. Whether patients *discharged* on weekends have worse clinical outcomes has been less well studied (13). Although daily discharge rates on Saturday and Sunday are lower than for the other five days of the week,(13) bed shortages and hospital overcrowding have increased interest in maximizing week-round discharge efficiency. Given that the proportion of patients discharged on weekend days is likely to continue to increase, assessing the risk of weekend discharge on outcomes is of paramount importance.

HF is one of the most common reasons for hospitalization and has a very high 30-day readmission risk(14). One previous study in HF patients found no association between discharge day of the week and 60 and 90 day death or rehospitalisation rates(15). However, potentially important prognostic factors, such as urgency of index admission (elective/non-elective), intensive care use, treatment by a specialist, and healthcare use within the previous year, were not examined in this study although all are now known to be important for adequate risk-adjustment for post-discharge outcomes.(16) In addition, the only published study did not examine hospital teaching status, a potentially important factor for post-discharge outcomes. The literature examining the association between hospital teaching status and outcomes is conflicting (17), although most studies have focused on in-hospital outcomes and only a few have examined post-discharge outcomes.

Thus, we designed this study to compare post-discharge outcomes for HF patients admitted to teaching hospitals (vs. non-teaching hospitals) and discharged on weekdays (vs. weekends). We hypothesized that both teaching status and weekday discharges would be associated with lower adjusted rates of 30-day death or readmission, and we hypothesized that the best outcomes would occur for patients admitted to a teaching hospital and discharged on a weekday.

Methods:

Study Setting:

The Canadian province of Alberta has a single vertically integrated health care system that is government-funded and provides universal access to hospitals, emergency departments, and outpatient physician services for all 3.7 million Albertans. The study received IRB approval from the University of Alberta (Pro00010852).

Data Sources:

This study used de-identified linked data from four Alberta Health administrative databases that capture all hospital, emergency department, and outpatient physician office visits. The Alberta Health Care Insurance Plan Registry tracks date of death or emigration from the province. The Discharge Abstract Database includes the most responsible diagnosis identified by the hospital attending physician, up to 24 other diagnoses coded by nosologists in each hospital, the admission and discharge dates, and the acuity (elective or non-elective) for all acute care hospitalizations. The Ambulatory Care Database captures all patient visits to Emergency Departments with coding for up to 10 conditions and the Health Practitioner Claims Database collects all outpatient physician visits and includes up to 3 diagnoses per encounter.

Study Cohort:

We identified all Albertans discharged after a hospitalization between January 1, 1999 and June 30, 2009 for a most responsible diagnosis of HF using ICD-9-CM code 428.x or ICD-10 code I50.x, codes previously shown to have high specificity (99%) and positive predictive value (91%) for HF when validated against chart audit in Alberta (18). We only selected each patient's first discharge with a most responsible diagnosis of HF.

We *a priori* defined teaching hospitals as the 8 hospitals in Alberta which had Royal College of Physicians and Surgeons of Canada-approved residency training programs in internal medicine and/or cardiology; the other 93 acute care hospitals in the province were classified as non-teaching. In a pre-planned sensitivity analysis, we restricted analyses to discharges in July of each year as prior studies have suggested that the influx of new housestaff with limited clinical experience at the beginning of each academic year is associated with decreased efficiency and poorer outcomes in teaching hospitals.(19) In essence, this sensitivity analysis attempted to control for the presence or absence of housestaff by exploring that time point during which they might have least positive influence on outcomes.

Outcomes:

Our primary outcome of interest was the composite outcome of death or all-cause non-elective readmission within 30 days of discharge; hereafter we refer to this as “death or readmission.” This is a patient-relevant outcome that is highlighted in the Affordable Care Act and advocated by the American Heart Association (AHA) Get With the Guidelines – Heart Failure (GWTG-HF) project; moreover, there is a validated risk adjustment model for this outcome.(20, 21) Secondary outcomes of interest included 90-day rates for the primary composite outcome and ED visits for any cause at 30 and 90 days.

Other Measures:

Comorbidities for each patient were identified using ICD-9 and ICD-10 codes from the Discharge Abstract Database for the index hospitalization and any hospitalizations in the 12 months prior to their index admission, a method previously validated in Alberta databases (16, 20, 21). We also recorded health resource use in the year prior to the index HF hospitalization and prognostically important features of the index HF hospitalization (including length of stay, intensive care unit requirements during the hospitalization, and treatment by a specialist during hospitalization).(16, 22, 23) ED utilization in the previous 6 months was recorded as it has previously been shown to be a risk factor for early readmission or death in HF patients.(16) The LACE score, an index for predicting unplanned readmission or early death post discharge previously validated in Canadian administrative databases, was recorded.(16, 24) Physicians were classified as specialists if their Alberta College of Physicians and Surgeons specialty was internal medicine or cardiology. Patients were classified as “rural” based on the postal code for their residence in the Alberta Health Care Insurance Plan Registry file(25).

Statistical Analysis

Patients were classified into 4 groups based on whether they were admitted to a teaching or a non-teaching hospital and discharged on a weekend or a weekday. Weekend discharge was defined as one occurring on a Saturday, Sunday, or a statutory holiday for hospitals within Alberta. We hypothesized that these 4 groups would represent a form of dose-response, with weekend discharge from a non-teaching hospital the reference group for all analyses.

Comparisons of baseline characteristics between the groups were performed using X^2 tests for categorical variables, and the Wilcoxon rank sum test or Analysis of Variance for continuous variables (when comparing median or mean, respectively). Cox proportional hazards models were used to compare the impact of discharges on weekends vs. weekdays for post-discharge death or readmission. Analysis was done for all hospitals, and then stratified by hospital teaching status (teaching vs. non-teaching). Multivariable models adjusted for the following variables: age, male sex, length of stay, index admission, Charlson comorbidity score (26), number of ED visits in previous 6 months, number of physician office visits in previous year, number of specialist office visits in previous year, rural residence , intensive care unit stay during index hospitalization, specialist consultation during index hospitalization, long term care admission during first 30 days after discharge, prior MI or revascularization, diabetes, dementia, atrial fibrillation, hypertension, chronic obstruction pulmonary disease, anemia, cerebrovascular disease, renal disease, cancer, and peripheral vascular disease. The interaction between teaching hospital and weekday discharge was assessed for our primary outcome and was not found to be significant (p=0.54 at 30 days and p=0.63 at 90 days) and was not included in the main model. Adjusted hazard ratios (HRs) were presented with their respective 95% confidence intervals (CI). We report 95% CI around these effect estimates, but we also examined 83% CI as 2 point estimates whose 83% CI do not overlap are statistically different with an alpha error of 5% or less.(27)

All statistical analyses were done using SAS version 9.3 (Cary, NC) and R version 2.12.2 (Vienna, Austria).

Role of the Funding Source:

This study was funded by a peer-reviewed operating grant from the Canadian Institutes of Health Research and Pfizer Canada (disease management industry partnership program). The funders had no input into study design, data collection, interpretation of results, or write-up/approval for submission.

Results:

Patient Characteristics

Over the 10-year follow-up period, 24,373 unique patients had at least one hospitalization with a most responsible diagnosis of heart failure (HF) and survived to discharge (Table 4.1). The mean age of this population was 76.3 years of age, 50.2% were men, and 25.7% lived in a rural area. Forty-nine percent of HF patients had at least one hospitalization in the previous 365 days but only 325 (1.3%) of these patients had a prior HF hospitalization.

Teaching vs. Non-Teaching Hospital Discharge

12,216 patients with HF were discharged from teaching hospitals and 12,157 adults were discharged from non-teaching hospitals (Figure 4.1). Patients discharged from teaching hospitals were younger, less likely to be rural residents, and less likely to have been hospitalized in the prior year than those from non-teaching hospitals. However, they received more outpatient care prior to admission and were more likely to see a specialist prior to and/or during the index hospitalization (Table 4.1). Although length of stay was approximately 2 days longer for patients in teaching hospitals, they were more likely to require intensive care unit support and they had substantially higher comorbidity burdens (particularly diabetes, hypertension, atrial fibrillation, and renal disease, Table 4.1). HF patients discharged from teaching hospitals exhibited lower rates of death or readmission than those discharged from non-teaching hospitals both at 30 days (17.4% vs. 22.1%, adjusted HR 0.83, 95% CI 0.77-0.89) and at 90 days (33.0% vs. 39.0%, adjusted HR 0.86, 95% CI 0.82-0.91) – Table 4.2, Figure 4.2. Similar patterns were seen for ED visits (Figure 4.3).

Weekday vs Weekend Discharge

Discharges were more common during weekdays: 85.7% in teaching hospitals and 86.6% in non-teaching hospitals (Figure 4.1). Only 2% of weekday discharges occurred on a statutory holiday and for the purposes of this study these discharges were considered weekend discharges. The mean number of discharges with HF as the most responsible diagnosis in Alberta were 7.7 (SD 3.4) on weekdays (ranging from means of 7.0 to 7.7 between Monday and Thursday and 9.9 on Fridays), 3.1 (SD 1.9) on weekends, and 3.8 (SD 2.5) on statutory holidays. Patients discharged on weekdays were older, had longer lengths of stay, were more likely to be discharged to a long term care facility, and had more comorbidities (Table 4.1). Despite their adverse risk profile, HF patients discharged on a weekday had lower 30-day rates of death or readmission than those discharged on a weekend (19.5% vs. 21.1%, adjusted HR 0.87, 95% CI 0.80-0.94) and lower 90-day rates of death or readmission (35.9% vs. 36.3%, adjusted HR 0.93, 95% CI 0.87-0.98) – Table 4.2, Figure 4.2. Similar patterns were seen for ED visits (Figure 4.3).

Conjoint Influence of Teaching Status and Day of Discharge

Using weekend discharge from a non-teaching hospital as the reference category and adjusting for an extensive list of covariates (see footnote to Table 4.2 for complete list), the risk of death or readmission at 30 days was statistically significantly lower in those patients discharged on a weekday from a non-teaching hospital (aHR: 0.85, 95%CI 0.77-0.94), on a weekend from a teaching hospital (aHR: 0.79, 95%CI 0.69-0.92), or on a weekday from a teaching hospital (aHR: 0.71, 95%CI 0.63-0.79) (Table 4.2, Figure 4.2). Analyses of the 83% CI around each of these point estimates revealed that even after adjusting for covariates, the risk of death or non-elective readmission was statistically significantly lower in patients discharged from teaching hospitals on weekdays (aHR 0.71, 83% CI 0.65-0.76) than non-teaching hospitals on weekdays (aHR 0.85, 83% CI 0.79-0.91). Similar patterns were seen for 90 day risk of death/non-elective readmission (Table 4.2) and 30 day/90 day risks of ED visits or non-elective readmission (Figure 4.3). In our pre-specified sensitivity analysis focusing only on the 1866 HF patients discharged in July over the decade we studied, patients discharged from teaching hospitals still exhibited lower risk of 30 day death/non-elective readmission (18.2% vs. 21.6%, aHR 0.72, 95% CI 0.56-0.94) than patients discharged from non-teaching hospitals.

Discussion:

In summary, we found that discharges from teaching (versus non-teaching) hospitals and on weekdays (versus weekends) had higher risk profiles but were associated with lower crude and adjusted risk of 30-day death or all-cause non-elective readmission. In an analysis stratified for both factors, we found a gradient of risk, whereby the adjusted risk was lowest for discharges on weekdays from teaching hospitals and highest for discharges on weekends from non-teaching hospitals. The relative excess risks attributable to being discharged from a non-teaching hospital or on a weekend were similar. While some may theorize that the better outcomes in teaching hospitals are due to the presence of housestaff, the fact that the associations were similar in July (when housestaff are inexperienced and less efficient) as in the other months of the year would argue against this being the sole factor. Indeed, our data would suggest that other mechanisms are in play at teaching hospitals that improve post-discharge outcomes beyond the mere presence of housestaff.

If our results are not a result of chance or bias or confounding, the potential factors that may explain the association between weekend discharges and increased risk include reduced staffing (for physicians, nurses and other allied health care workers), physician cross-coverage, incomplete handover between professional care givers, limited support services (such as consultation services or diagnostic imaging), and decreased availability of community services (including home care and social support services).(1, 3, 13, 28) For example, in the GWTG-HF Registry, HF patients discharged on a weekend received less complete discharge instructions than those discharged on weekdays and were less likely to have their left ventricular ejection fraction measured.(6)

To our knowledge, only the OPTIMIZE-HF registry, which included 48 612 patients from 259 US hospitals, examined day of discharge and post-discharge outcomes and they reported no differences in 60 and 90 day death or rehospitalisation rates after discharge regardless of day of the week(15). These investigators studied registry patients as opposed to a population based sample and they did not examine teaching status of hospitals or other factors known to influence risk of post-discharge outcomes such as urgency of index admission (elective/non-elective), intensive care use, treatment by a specialist, and healthcare use prior to the hospitalizaton. Thus, we believe our study adds novel insights to the literature on this topic.

Although we were able to include data for all interactions with the health care system in a single payer system with universal free access, there are some limitations to our study. First, we used administrative data, which precludes fully adjusting for severity of HF or functional status although we used proxies such as need for ICU support or specialist involvement during the hospitalization and admission from/discharge to long term care facility.(29, 30) Second, although the baseline characteristics differed between those HF patients discharged from teaching hospitals and those discharged from non-teaching hospitals, teaching hospital patients actually exhibited a greater burden of disease such that the differences would have been expected to bias our study findings towards the null. Third, although we limited our comparisons between hospitals to those with and without teaching programs, we recognize that independent of teaching status, hospitals that participate in clinical trials (and other facets of the academic enterprise) tend to deliver better quality of care and achieve better outcomes than those which do not so participate(31). Fourth, we did not have access to diagnostic testing or prescribing data and thus cannot determine whether patients discharged from teaching hospitals received better quality of care or if these patients were more adherent with evidence-based prescriptions or testing recommendations. Finally, and most importantly, we acknowledge that death or readmission soon after discharge for HF patients does not necessarily mean that the quality of care during the preceding hospitalization was suboptimal or that these deaths or readmissions were even potentially preventable. Many factors influence post-discharge mortality and/or readmission and quality of inpatient care is only one(32, 33).

Conclusion:

We found that patients with HF who were discharged from a teaching hospital and discharged during the week had the best outcomes, despite having higher risk profiles. The structures and processes of care involved in weekday discharges from teaching hospitals should be studied in more detail to identify key factors that could be emulated in order to optimize outcomes for all patients with HF.

Table 4.1. Baseline characteristics of patients discharged after a first time hospitalization for a most responsible diagnosis of HF

Patient characteristics	Teaching Hospitals				Non-teaching hospitals				p value for comparison of discharges in teaching vs. non-teaching hospitals
	Weekday (Monday-Friday) Discharges	Weekend Discharges (Saturday-Sunday)	p value for comparison of weekday vs. weekend in teaching hospitals	Total Discharges	Weekday (Monday-Friday) Discharges	Weekend Discharges (Saturday-Sunday)	p value for comparison of weekday vs. weekend in non-teaching hospitals	Total Discharges	
Patients	**10469 (85.7)**	**1747 (14.3)**		**12,216**	**10532 (86.6)**	**1625 (13.4)**		**12,157**	
Male	5275 (50.4)	928 (53.1)	0.03	6203 (50.8)	5213 (49.5)	811 (49.9)	0.76	6024 (49.6)	0.06
Mean age (SD)	75.5 (12.6)	73.3 (13.1)	<.0001	75.2 (12.7)	77.5 (11.4)	76.4 (11.6)	0.0002	77.4 (11.4)	<.0001
Rural residence	628 (6.0)	130 (7.4)	0.02	758 (6.2)	4754 (45.1)	743 (45.7)	0.66	5497 (45.2)	<.0001
Health Resource Use:									
At least one ED visit previous 6 months	7048 (67.3)	1085 (62.1)	<.0001	8133 (66.6)	6744 (64.0)	1050 (64.6)	0.6490	7794 (64.1)	<.0001
Mean number of ED visits previous 6 months (SD)	1.6 (2.1)	1.4 (1.9)	<.0001	1.5 (2.1)	2.0 (3.6)	2.0 (2.7)	0.3194	2.0 (3.5)	<.0001
At least one hospitalization previous 365 days	4689 (44.8)	745 (42.6)	0.09	5434 (44.5)	5610 (53.3)	863 (53.1)	0.91	6473 (53.2)	<.0001
Mean number of hospitalizations previous 365 days (SD)	0.8 (1.2)	0.8 (1.1)	0.31	0.8 (1.2)	1.2 (1.7)	1.2 (1.7)	0.50	1.2 (1.7)	<.0001
Mean number of physician office visits previous 365	14.9 (12.1)	15.4 (12.8)	0.07	15.0 (12.2)	12.7 (9.6)	12.8 (9.4)	0.59	12.7 (9.6)	<.0001

days (SD)									
Specialist office visit for any cause in previous 365 days	6113 (58.4)	1063 (60.8)	0.05	7176 (58.7)	3697 (35.1)	574 (35.3)	0.86	4271 (35.1)	<.0001
Specialist saw during index hospitalization	8609 (82.2)	1482 (84.8)	0.008	10091 (82.6)	3467 (32.9)	450 (27.7)	<.0001	3917 (32.2)	<.0001
Specialist visit during index hospitalization or previous 365 days	9535 (91.1)	1627 (93.1)	0.005	11162 (91.4)	5545 (52.6)	812 (50.0)	0.04	6357 (52.3)	<.0001
ICU admission during index hospitalization	1897 (18.1)	465 (26.6)	<.0001	2362 (19.3)	1680 (16.0)	224 (13.8)	0.03	1904 (15.7)	<.0001
Median length of stay for index HF hospitalization (IQR)	10 (6, 16)	8 (5, 13)	<.0001	9 (6, 16)	8 (5, 14)	6 (4, 10)	<.0001	7 (5, 13)	<.0001
Mean Charlson during index hospitalization (SD)	4.3 (2.1)	4.1 (1.9)	<.0001	4.3 (2.1)	4.2 (2.1)	4.0 (1.9)	0.002	4.2 (2.1)	<.0001
Mean LACE score at time of index HF hospitalization discharge (SD)	13.6 (2.5)	12.9 (2.5)	<.0001	13.5 (2.5)	13.2 (2.7)	12.7 (2.7)	<.0001	13.2 (2.7)	<.0001
Admitted to long-term care facility within 30 days of discharge	1092 (10.4)	75 (4.3)	<.0001	1167 (9.6)	576 (5.5)	48 (3.0)	<.0001	624 (5.1)	<.0001
Comorbidities at time of discharge from index HF hospitalization (based on index hospitalization and prior 12 months):									

Diabetes	3783 (36.1)	639 (36.6)	0.72	4422 (36.2)	3563 (33.8)	519 (31.9)	0.13	4082 (33.6)	<.0001
Hypertension	6636 (63.4)	1095 (62.7)	0.57	7731 (63.3)	5323 (50.5)	823 (50.6)	0.94	6146 (50.6)	<.0001
Dementia	889 (8.5)	87 (5.0)	<.0001	976 (8.0)	768 (7.3)	82 (5.0)	0.0010	850 (7.0)	0.003
COPD	4033 (38.5)	622 (35.6)	0.02	4655 (38.1)	4153 (39.4)	620 (38.2)	0.33	4773 (39.3)	0.06
Anemia	2971 (28.4)	408 (23.4)	<.0001	3379 (27.7)	2270 (21.6)	348 (21.4)	0.90	2618 (21.5)	<.0001
CVD	1065 (10.2)	146 (8.4)	0.02	1211 (9.9)	1025 (9.7)	146 (9.0)	0.34	1171 (9.6)	0.46
Renal disease	2505 (23.9)	360 (20.6)	0.002	2865 (23.5)	1572 (14.9)	219 (13.5)	0.13	1791 (14.7)	<.0001
Cancer	629 (6.0)	100 (5.7)	0.64	729 (6.0)	797 (7.6)	118 (7.3)	0.66	915 (7.5)	<.0001
PVD	1228 (11.7)	194 (11.1)	0.45	1422 (11.6)	1114 (10.6)	150 (9.2)	0.10	1264 (10.4)	0.002
Atrial fibrillation	4538 (43.3)	770 (44.1)	0.57	5308 (43.5)	3744 (35.5)	504 (31.0)	0.0004	4248 (34.9)	<.0001
Prior MI or prior revascularization	2978 (28.4)	492 (28.2)	0.81	3470 (28.4)	2032 (19.3)	324 (19.9)	0.54	2356 (19.4)	<.0001
Prior MI	2861 (27.3)	465 (26.6)	0.54	3326 (27.2)	1964 (18.6)	312 (19.2)	0.60	2276 (18.7)	<.0001
Prior revascularization	391 (3.7)	78 (4.5)	0.14	469 (3.8)	237 (2.3)	41 (2.5)	0.49	278 (2.3)	<.0001

Numbers are n (%) unless specified otherwise

Figure 4.1. Derivation of cohorts

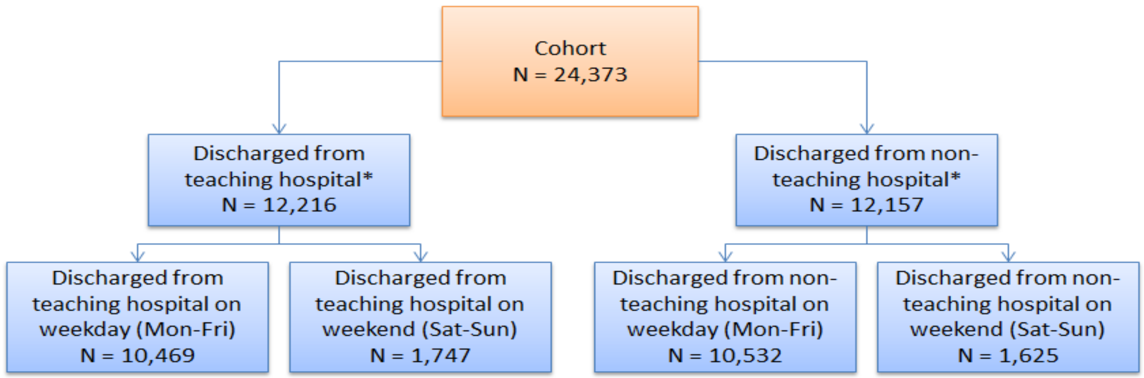


Table 4.2. Death or non-elective readmission after discharge with a most responsible diagnosis of HF

Death/non-elective readmission after index hospital discharge:	Proportion having an event	Events per 100 patient years	Unadjusted HR (95% CI)	Adjusted HR (95% CI)†	Adjusted HR (83% CI)
At 30 days					
Non-teaching hospital discharge (any day)	22.1%	308	1 (ref)	1 (ref)	1 (ref)
Teaching hospital discharge (any day)	17.4%	233	0.76 (0.72, 0.81)	0.83 (0.77, 0.89)	0.83 (0.79, 0.87)
At 30 days					
Weekend/holiday discharge from any hospital	21.1%	292	1 (ref)	1 (ref)	1 (ref)
Weekday discharge from any hospital	19.5%	266	0.91 (0.84, 0.98)	0.87 (0.80, 0.94)	0.87 (0.82, 0.91)
At 30 days					
Weekend/holiday discharge from non-teaching hospital	24.3%	345	1 (ref)	1 (ref)	1 (ref)
Weekday discharge from non-teaching hospital	21.7%	301	0.87 (0.79, 0.97)	0.85 (0.77, 0.94)	0.85 (0.79, 0.91)
Weekend/holiday discharge from teaching hospital	18.1%	244	0.71 (0.62, 0.81)	0.79 (0.69, 0.92)	0.79 (0.72, 0.88)
Weekday discharge from teaching hospital	17.2%	232	0.67 (0.61, 0.75)	0.71 (0.63, 0.79)	0.71 (0.65, 0.76)
At 90 days					
Non-teaching hospital discharge (any day)	39.0%	211	1 (ref)	1 (ref)	1 (ref)
Teaching hospital discharge (any day)	33.0%	168	0.80 (0.77, 0.84)	0.86 (0.82, 0.91)	0.86 (0.83, 0.90)

At 90 days					
Weekend/holiday discharge from any hospital	36.3%	193	1 (ref)	1 (ref)	1 (ref)
Weekday discharge from any hospital	35.9%	188	0.98 (0.92, 1.04)	0.93 (0.87, 0.98)	0.93 (0.89, 0.96)
At 90 days					
Weekend/holiday discharge from non-teaching hospital	40.2%	222	1 (ref)	1 (ref)	1 (ref)
Weekday discharge from non-teaching hospital	38.8%	209	0.94 (0.87, 1.02)	0.91 (0.84, 0.99)	0.91 (0.86, 0.96)
Weekend/holiday discharge from teaching hospital	32.6%	167	0.76 (0.68, 0.84)	0.84 (0.75, 0.94)	0.84 (0.78, 0.91)
Weekday discharge from teaching hospital	33.0%	169	0.77 (0.71, 0.83)	0.79 (0.72, 0.86)	0.79 (0.74, 0.84)

†Multivariable models adjusted for the following variables: age, male, index hospitalization for length of stay, non-elective index admission, Charlson comorbidity score (26), number of ED visits in previous 6 months, number of physician office visits in previous year, if seen by specialist during office visit in previous year, rural postal code, intensive care unit stay during index hospitalization, saw specialist during index hospitalization, long term care admission during first 30 days after discharge, prior MI or revascularization, diabetes, dementia, atrial fibrillation, hypertension, chronic obstruction pulmonary disease, anemia, cerebrovascular disease, renal disease, cancer, and peripheral vascular disease.

Figure 4.2. Survival curves for time to death or non-elective readmissions in HF patients stratified by day of discharge and hospital-teaching status.

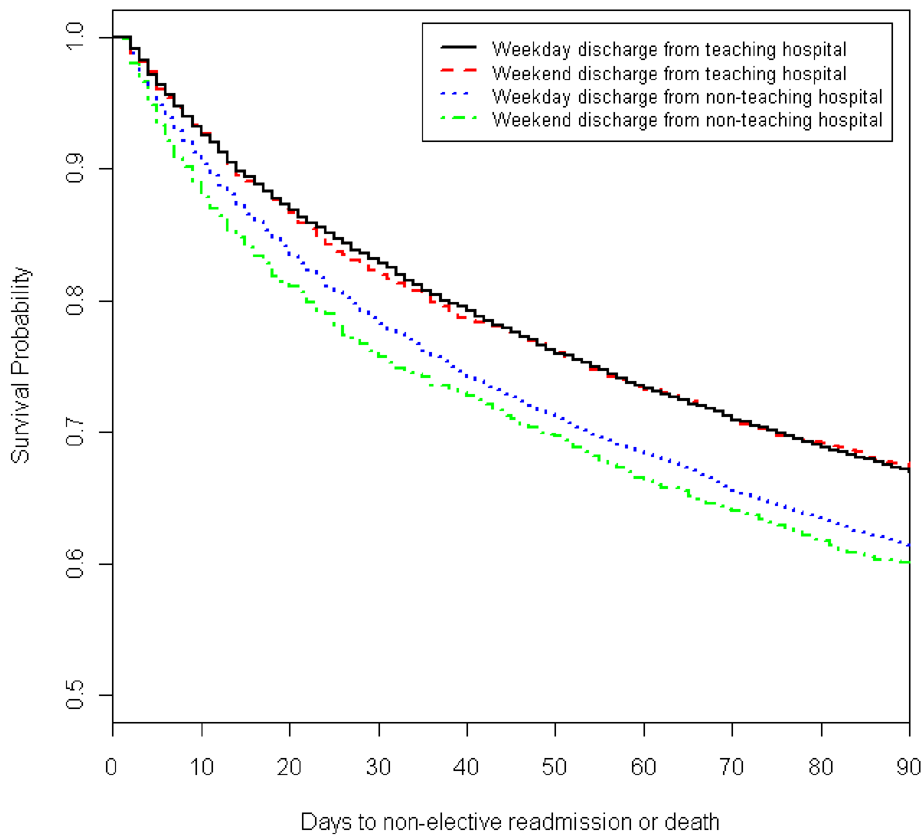
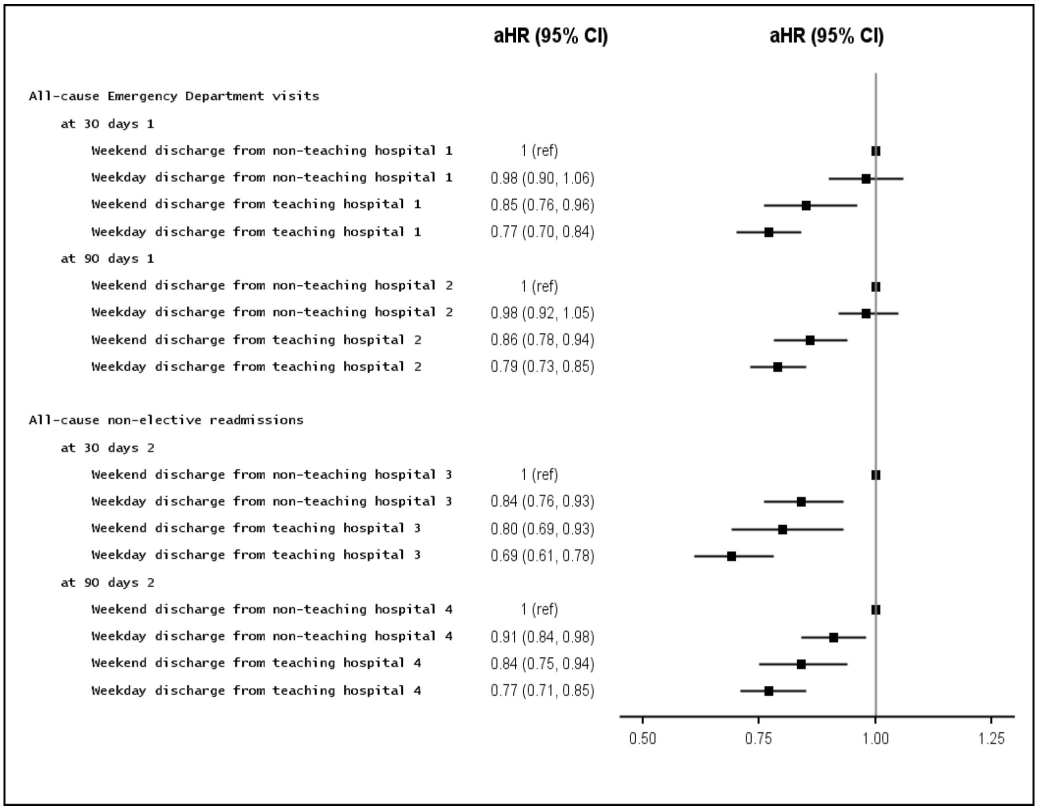


Figure 4.3. Forest plot of risk of all-cause ED visit after hospital discharge



†Multivariable models adjusted for the following variables: age, male, index hospitalization for length of stay, non-elective index admission, Charlson comorbidity score (26), number of ED visits in previous 6 months, number of physician office visits in previous year, if seen by specialist during office visit in previous year, rural postal code, intensive care unit stay during index hospitalization, saw specialist during index hospitalization, long term care admission during first 30 days after discharge, prior MI or revascularization, diabetes, dementia, atrial fibrillation, hypertension, chronic obstruction pulmonary disease, anemia, cerebrovascular disease, renal disease, cancer, and peripheral vascular disease.

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Chapter 5: General Discussion/Conclusion

Readmissions represent a significant portion of hospitalizations and pose a substantial burden on the healthcare system. Indeed, our finding of 21% risk of 30 day death or readmission for HF patients in Alberta is consistent with other HF studies (1, 2). Accurate predictive scoring systems for HF and other medical conditions are appealing to government and healthcare funding agencies to risk adjust and thereby compare hospital performance in treating certain common medical conditions. From a health care provider's standpoint, the ability to accurately predict which patients are at high risk of admissions would allow for more targeted interventions and closer follow-up aimed at this population. However, in order to do so, accurate scoring systems will need to be derived.

The findings from the *Predicting the risk of unplanned readmission or death within 30 days of discharge after a heart failure hospitalization* study shows that the models currently used by the CMS to predict heart failure readmissions are only moderately useful at predicting heart failure readmissions in the Alberta population. While the LaCE index, with a c-statistic of 0.61, fared only slightly better than the CMS models (c-statistic of 0.59 Krumholz model and 0.60 Keenan model) and Charlson comorbidity index (c-statistic 0.55), for predicting HF readmissions, it was significantly better able to predict the composite of death or unplanned readmissions within 30 days of discharge with a NRI of 19.1% compared with the CMS model by Keenan.. Thus, while the LaCE index may be useful to risk adjust post-discharge outcome rates for comparisons between hospitals (or in the same hospital over time), it lacks the discriminative ability needed for patient level risk prediction such as the $CHADS_2$ scoring system to predict stroke in patients with non-valvular atrial fibrillation with a c-statistic of 0.82)(3) or the Framingham risk score to predict the 10 year risk of myocardial infarction and coronary death with c-statistics of and 0.73 for men and 0.76 for women).(4)

In addition to formal prediction scoring systems, informal predictions by healthcare providers for death and readmission have also been studied in a variety of settings including the intensive care unit (ICU)(5, 6) (5, 6), internal medicine wards(7, 8), and cardiology wards (9-11). ICU physicians may be better at predicting 24 hour mortality in ICU patients compared to scoring systems with an ROC of 0.85.(5) On internal medicine wards, neither healthcare providers nor published algorithms were able to predict patients at risk of readmission.(7) Interestingly, while nurses and physicians were found to only be moderately accurate at predicting readmissions and death in the HF patients with ROC 0.675 and 0.603, respectively, compared with a prognostic model of 0.603, the combination of nurse prediction and the predictive model increased the c-statistic to 0.703 but not the combination of physician + predictive model.(9) The NRI was not used in this study which would have been more useful to report.

Furthermore, while most scoring systems incorporated variables which included use of prior medical services and medical comorbidities, a systematic review of 26 risk prediction models found that few included variables for illness severity, overall health and function or social determinants of health and most prediction models performed poorly. (12) Access to primary care post-discharge (12), caregiver problems(13), living alone (13), and lower socioeconomic status (14) have all been found to contribute to readmission risk but are rarely included in predictive scoring systems. Future models that use both administrative data, combined with clinical variables which take into account illness severity and overall health and function and social factors into consideration may be more accurate.

In a resource-limited environment, the most efficient way for intervention programs to be effective is if they are targeted in areas where a difference can be made, in this case, towards patients at risk of a potentially avoidable readmission, instead of all-cause readmissions. However, the majority of current prediction scoring systems, including those used in general internal medicine(15, 16), are used to predict all-cause readmissions. In Ontario, a multicentre prospective cohort study found that only 16% of all urgent readmissions to hospital in a medical and surgical cohort were potentially avoidable readmissions making it a relatively uncommon event. (17) Two systematic reviews have found a wide-range of reported avoidable readmissions in the literature ranging between 5-79%.(17, 18) The SQLape(Striving for Quality Level and

Analyzing of Patient Expenses) is a computer-based algorithm developed in Switzerland which estimates potentially avoidable readmissions. A study of 49 Swiss hospitals showed the SQLape to be fairly discriminative for predicting a potential avoidable readmission with a C-statistic of 0.72.and a positive predictive value of 78%.(19) Potentially avoidable readmissions were defined as: *readmissions related to a condition of the previous hospitalization and not expected as part of a program of care and occurring within 30 days after previous discharge.* A very recently published prediction scoring system called the HOSPITAL score attempted to identify patients at high risk of a potentially avoidable 30-day readmission in a general internal medicine population.(20) This study identified potentially avoidable readmission identified using the SQLape computer algorithm and confirmed the avoidable nature of these admissions by review with trained senior medical residents. The scoring system includes the variables: *h*aemoglobin at discharge, discharge from an *o*ncology service, *s*odium level at discharge, *p*rocedure during the index admission, *i*ndex *t*ype of admission, number of *a*dmissions during the last 12 months, and *l*ength of stay. It incorporated 2 variables which are part of the LACE index. The HOSPITAL scoring system had fair discriminatory ability with a C-statistic of 0.71, correctly identified 99% of the high risk patients who were readmitted, and 88% of low risk patients who were readmitted. It requires external validation in other populations and, if found to be valid, offers promise as a tool to help identify patients at high risk for potentially avoidable readmission and perhaps therefore a more efficient way of targeting interventions.

In addition to predicting all-cause readmissions rather than avoidable readmissions, most current models are generally focused on predicting readmission risk for those individuals discharged to the community. Populations such as those residing in a nursing home or discharged to a rehabilitation facility are excluded, as was the case for the derivation of the LACE index and in our study. Processes of care in nursing homes(21) and rehabilitation facilities may differ from those in the community (including the presence of on-site physicians which may avert a readmission or the presence of advance care directives mandating against transfer to an acute care hospital even if the patient deteriorates). Residing in a nursing home is a risk factor for readmission,(22, 23) independent of age (22, 23), cognitive status (22) or number of chronic medical conditions (23) as confirmed by multivariate analysis suggesting that it may not just be a marker for sicker, older or more frail patients and may be related to processes of care in the nursing homes themselves. This is an area where further research would be useful. deserves further research into this area.

Multiple factors contribute to risk of readmissions beyond simply quality of inpatient care. While factors such as patient case mix (24, 25), disease severity (25-27) and functional status (12) would be important contributors to readmissions, other medical, social and environmental factors are also important contributors. As a result, there are various areas in which targeted interventions can be applied. While improved communication between hospitalist and a patient's regular physician by way of a timely delivery of discharge summary resulted in a trend toward decreased risk for patients who received follow-up by a physician who had received a summary,(28) direct communication between a patient's inpatient and outpatient provider was not found to be associated with readmission risk for patients discharged from a medical service(29), The timeliness of post-discharge follow-up (30), quality of medication reconciliation, and effective physician-patient communication at the time of discharge are also associated with readmission risk. (31) In specific medical populations such as HF, comprehensive discharge planning and follow-up has also been shown to reduce readmissions and be cost effective. (32, 33) In a systematic review looking at interventions to reduce HF readmissions, multidisciplinary strategies including follow-up with specialized multidisciplinary teams, programs focused on enhancing patient self-care activities and telephone contact advising patients to attend their primary care physician in the event of deterioration of HF were all beneficial in reducing hospitalizations.(34)

In order to maximize the potential for success of interventions to reduce readmissions, five strategies have been proposed by Burke and Coleman(35) including identifying a patients risk of readmission and matching the intensity of interventions to match the risk, avoiding the use of unproven interventions, selecting interventions that will lead to a lasting effect, establishment of effective teams prior to implementation of any interventions, and finally, the broadening of interventions to include previously unrecognized patient groups at high risk of readmission who have not been the focus of previous readmission reduction efforts. This thesis has focused on the first and fifth points raised by Burke and Coleman.

In addition to pursuing further research into the development of more accurate risk prediction models which focus on avoidable readmissions, other studies which look at pre and post-discharge care would be of importance. For example, to further investigate what we found regarding outcome differences between teaching and non-teaching hospitals for patients with a diagnosis of HF, assessing the adherence to treatment guidelines for HF would be of interest to determine if that is a possible reason for the differences. A study which studies quality of care outcomes pre- and post- an intervention on general internal medicine wards would also be of interest. For example, at the University of Alberta Hospital, an integrated care plan known as the Care Transformation Initiative was instituted in August 2011 for all GIM ward patients with the aim of improving patient care. It consisted of 28 interventions in the areas of demand capacity re-alignment, interprofessional collaboration, implementation of best practises (clinical practice guidelines and accreditation standards) and transitional optimizations using interprofessional teams. This would be an ideal area to study whether these interventions have been effective in changing clinical outcomes.

Policy implications

The fact that not all readmissions are potentially avoidable has implications for health care policy makers. If the majority of readmissions are considered unavoidable and not attributable to the quality of care received during the index admission, then the decision to evaluate and compare hospital performance on all –cause readmission rates is flawed. As such, the decision to penalize those hospitals who exceed the expected risk-adjusted all-cause readmission rate seems unfair. Furthermore, hospitals located in inner-city neighbourhoods or who care for indigent populations or those at the lowest socioeconomic status would be most at risk for penalties as studies show that these populations are at higher risk for medical readmissions. (36-38)

In a conceptual model of all readmissions and potentially avoidable readmissions, van Walraven and Forster(39) argue that if 22% of readmissions are considered potentially avoidable, a 20 % reduction in all-cause readmission (as is the current goal by CMS) would require a 91% reduction in potentially avoidable readmissions. On the other hand, a 20% reduction in potentially avoidable readmissions would only result in a 4.4% reduction in all-cause readmissions. The first situation is likely unattainable and the second situation may not result in large cost-savings. Thus until accurate methods to measure potentially avoidable readmission rates are developed and risk prediction models to accurately target those patients at highest risk of an avoidable readmission are developed, it seems premature to penalize hospitals to try to stimulate change.

In conclusion, readmissions are a significant contributor to hospital costs and cannot be predicted with a high degree of accuracy. They are common and affected by multiple factors beyond simply the quality of inpatient care. Indeed, preventable readmissions represent only a minority of all readmissions and there are no risk prediction models for "preventable" readmissions. Thus, at the present time, interventions designed to improve post-discharge outcomes must remain targeted at all patients rather than just "high risk" patients, thereby reducing their efficiency and cost-effectiveness. Priorities for future research include the accurate identification of those patients at highest risk of preventable post-discharge outcomes (including previously ignored groups such as those being discharged to long term care facilities), the development of simple predictive scoring systems to identify these "high risk" individuals, and the development of effective interventions for specific patient populations.

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