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Predicting readmission risk following percutaneous coronary intervention at the time of admission

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ABSTRACT

Objective: To investigate whether a prediction model based on data available early in percutaneous coronary intervention (PCI) admission can predict the risk of readmission.**Background:** Reducing readmissions following hospitalization is a national priority. Identifying patients at high risk for readmission after PCI early in a hospitalization would enable hospitals to enhance discharge planning.**Methods:** We developed 3 different models to predict 30-day inpatient readmission to our institution for patients who underwent PCI between January 2010 and April 2013. These models used data available: 1) at admission, 2) at discharge 3) from CathPCI Registry data. We used logistic regression and assessed the discrimination of each model using the c-index. The models were validated with testing on a different patient cohort who underwent PCI between May 2013 and September 2015.**Results:** Our cohort included 6717 PCI patients; 3739 in the derivation cohort and 2978 in the validation cohort. The discriminative ability of the admission model was good (C-index of 0.727). The c-indices for the discharge and cath PCI models were slightly better. (C-index of 0.751 and 0.752 respectively). Internal validation of the models showed a reasonable discriminative admission model with slight improvement with adding discharge and registry data (C-index of 0.720, 0.739 and 0.741 respectively). Similarly validation of the models on the validation cohort showed similar results (C-index of 0.703, 0.725 and 0.719 respectively).**Conclusion:** Simple models based on available demographic and clinical data may be sufficient to identify patients at highest risk of readmission following PCI early in their hospitalization.

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1. Introduction

Percutaneous coronary intervention (PCI) is among the most common major medical procedures in the U.S. [1]. Despite the improvement of care over time, a significant number of Medicare patients (14.6%) are readmitted after PCI [2,3]. The Patient Protection and Affordable Care Act linked many quality outcomes including 30-day readmission rates to hospital reimbursement [4]. The Center for Medicare and Medicaid Services (CMS) publicly reports hospital level 30-day readmission rates for heart failure (HF), acute myocardial infarction (AMI) [1,5,6]. As a quality measure many hospitals are interested not only in reducing readmissions after AMI or HF exacerbation, but also after elective procedure like PCI.

With these changing incentives, many health systems are developing programs to improve the quality of transitional and longitudinal care upon discharge. Research suggests that multi-component

interventions that focused on transitional care can reduce the readmission rates in certain conditions, including PCI [7]. However, for these programs to be cost-effective, it will be necessary to target efforts to the patients that are most likely to benefit from the increased intensity of services. Additionally, services may be most effective if they begin during the hospitalization so that the care quality and patient education can be maximized during the hospital stay [5].

Although many studies have identified strong predictors for readmissions risk following PCI [3,8,9], to date there are only two risk models designed so far to specifically predict readmission risk for patients undergoing PCI [10,11]. However although these risk models used registry data available early in the admission or discharge to identify patients at high risk for readmission, they did not address the possibility of using data readily available prior to or at the time of admission to predict readmission risk at the minute of index admission.

We sought to develop a model to predict readmission risk following PCI using clinical and administrative data available within our hospital system at the time of admission, and to determine the incremental benefit to risk assessment of adding 1) clinical information available at the time of discharge, and 2) registry data from the CathPCI Registry. Our

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findings will inform the use of clinical data within hospital systems to prospectively risk-stratify patients to support the cost-effective application of care management or other resources with the intent to reduce readmission.

2. Methods

2.1. Study design, population, and setting

We conducted a retrospective cohort of all patients with revascularization with PCI at Christiana Care Health System between January 1, 2010 and September 30, 2015. Christiana Care is a large system that comprises two hospitals with more than 1100 beds as well as a variety of outpatient and other services in facilities and provides the majority of cardiovascular care in Delaware and the surrounding area with an estimate of 1700 PCI and more than 600 open heart surgery procedures annually. We identified all patients who were discharged alive following PCI. We further divided the cohort into 1) a derivation cohort that was used to develop the 3 separate prediction models and included PCI patients admitted between April 1, 2010 and April 30, 2013; and 2) a validation cohort that was used to test the prediction models and included those admitted between May 1, 2013 and September 30, 2015. Importantly, the validation cohort included patients that were included in a longitudinal care management program for patients following coronary revascularization. Patients were enrolled in the program during the hospitalization and followed with telephonic care management following discharge. The Christiana Care Institutional Review Board approved the study.

2.2. Outcomes

We identified inpatient, non-elective readmissions to Christiana Care within 30 days of discharge from the index procedure. We excluded elective readmissions such as staged PCIs based on admission records. We excluded patients who were who received coronary artery bypass surgery during the same admission. We identified readmissions at our own system and we used QualityNet Data from CMS to identify readmissions at other hospitals.

2.3. Candidate variables and model derivation

Candidate variables for the prediction model were drawn from three sources: 1) administrative and billing data from the data warehouse at Christiana Care (demographics, previous utilization, and comorbidities); 2) clinical data including initial and discharge laboratory and vital signs from key clinical systems; and 3) registry information from the NCDR CathPCI Registry for data concerning anatomic and procedural information. Comorbidities were classified from administrative data using the Elixhauser classification [12].

In order to determine the incremental value of additional information gathered across the hospital visit, we developed the following three models that sequentially added information available during the hospitalization: 1) an admission model that included only variables available at the time the patient arrived at the hospital, 2) a discharge model that included administrative and clinical information available at the time of discharge; and 3) a discharge model that also included anatomic and procedural information from the CathPCI Registry. This progression of models was chosen based on the timing of availability of these data in the clinical setting. The CathPCI registry information, for example, is collected by staff following discharge and is not available for operational purposes at the time of discharge. These variables and the progress in building each model are shown in Table 1.

Hierarchical logistic regression was used to model readmissions (a patient may have had more than one PCI during the study period). Derivation models were developed by a combination of forward selection and backward elimination of variables. Variables were entered if

Table 1

Variables by data class and sequential model development.

Variables by data class		
Baseline/Admission	Discharge	Cath PCI Registry
Age	Length of stay	Any complication
Sex	AMI indication	LVEF at discharge
Race	Any ICU stay	Pre-TIMI flow
Insurance	Weekend discharge	Cerebral vascular disease
Elective status	Discharge location	Artery access location:
	Home	Femoral
	Home with services	Radial
	Skilled nursing Facility	Other
	Others facility	Lesion count ≥ 2
Previous PCI	Elixhauser	High lesion complexity
Previous CABG	Comorbidities	Beta blocker
Weekend admission	• Comorbidity count	ACEI/ARB
Previous hospitalization	• CHF	Antiplatelet type
Previous AMI	• COPD	(Clopidogrel/Prasugrel/Ticagrelor)
	• Diabetes	Canadian Classification System Angina Class
	• Renal failure	Angina type:
	• Perivascular disease	No symptoms
	• Valve disease	Stable angina
	• Electrolyte Imbalance	Unstable angina
	• Obesity	NSTEMI
		STEMI
Model	Data classes included	
1	Baseline - Admission	
2	Baseline - Admission/Discharge	
3	Baseline - Admission/Discharge/Cath PCI Registry	

All variables in each set were initially entered into the model and then removed by elimination criteria.

Variables retained in each model were retained in the subsequent model.

Abbreviations: PCI = percutaneous intervention AMI = acute myocardial infarction. LVEF = left ventricle ejection fraction ICU = intensive care unit. TIMI = thrombolysis in myocardial infarction ACEI = angiotensin converting enzyme inhibitor. ARB = angiotensin receptor inhibitor CABG = coronary artery bypass grafting COPD = chronic obstructive pulmonary disease. NSTEMI = non-ST elevation myocardial infarction STEMI = ST elevation myocardial infarction.

$p \leq .2$ and removed if $p > .2$. Reduced models were compared to larger models by likelihood ratio tests. Fractional polynomial (FP) regression was used to assess non-linearity of continuous variables. Cubic splines were then used to determine categories for nonlinear continuous variables. Although adding variables to the sequential models will likely change the estimation of odds ratios (as well as contribution to the predictive ability of the model), variables were retained in subsequent models regardless of their contribution to predictive ability. Model discrimination was assessed by the c-statistic and model calibration was assessed by plotting observed readmission rates with deciles of model-predicted rates.

Models were developed for PCI patients admitted to the hospital between April 1, 2010 and April 30, 2013. Internal model validity was assessed by bootstrap methods – 500 bootstrap replicates with replacement were drawn to calculate bias-corrected c-indices. The derivation models were then applied to patients admitted between May 1, 2013 and September 30, 2015 to assess external validity.

3. Results

The total number of PCI patients was 6717 including 3739 in the derivation cohort and 2978 in the validation cohort. These patients had a total of 7749 hospitalizations; 4340 in the derivation cohort and 3409 in the validation cohort. The readmission rate was 8.4%. The 30-days readmission rate was 8.5% and The 30-days mortality was very low at 0.5%. Table 2 shows the demographic and clinical characteristics of the derivation and validation cohorts.

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