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Development and validation of a predictive model for all-cause hospital readmissions in Winnipeg, Canada

Yang Cui[1,2,3], Colleen Metge[1,2,3], Xibiao Ye[1,2,3], Michael Moffatt[1,2,3], Luis Oppenheimer[4,5] and Evelyn L Forget[3]

Abstract

Objective: A number of predictive models have been developed to identify patients at risk of hospital readmission. Most of these have focused on readmission within 30 days of discharge. We used population-based health administrative data to develop a predictive model for hospital readmission within 12 months of discharge in Winnipeg, Canada.

Methods: This was a retrospective cohort study with derivation and validation data sets. Multivariable logistic regression analyses were performed and factors significantly associated with readmission were selected to construct a risk scoring tool.

Results: Several variables were identified that predicted readmission (i.e. older age, male, at least one hospital admission in the previous two years, an emergent (index) hospital admission, Charlson comorbidity score >0 and length of stay). Discrimination power was acceptable (C statistic =0.701). At a median risk score threshold, the sensitivity, specificity, positive and negative predictive values were 45.5%, 79%, 68.8% and 58.6%.

Conclusions: This predictive model demonstrated that hospital readmission within 12 months of discharge can be reasonably well predicted based on administrative data. It will help health care providers target interventions to prevent unnecessary hospital readmissions.

Keywords

hospital readmission, predictive model, risk factor

Introduction

Rapidly rising health care costs have become a concern for many countries including Canada. In Canada, total health care spending exceeded $200 million in 2011.[1] Driven by population aging, new technologies, inflation and other factors, health care costs are anticipated to continue to increase. Thus, health care planners are exploring options for improving health care spending efficiency, system performance and quality of care in the health care system. Much of the focus has been directed towards hospitalization in general. Reducing hospital readmissions has been posited to be one of the means for reducing costs of health care and improving patient outcomes. Hospital readmissions contribute a large percentage of inpatient costs to the health care system. It was estimated that the costs of readmissions were $1.8 billion per year.[2] Studies have shown that between 9% and 59% of readmissions were potentially avoidable by improving care before and after discharge.[3] Reducing hospital readmissions has been considered as a key area to improve efficiency.[4,5]

Despite the necessity of reducing hospital readmissions, it is not feasible if a focused post-discharge intervention for readmission target all discharged patients due to health care resource constraints. The intervention will be more effective and sustainable if high-risk patients are accurately identified and targeted.

[1]The George and Fay Yee Centre for Healthcare Innovation, Winnipeg, Manitoba, Canada
[2]Winnipeg Regional Health Authority, Winnipeg, Manitoba, Canada
[3]Department of Community Health Sciences, Faculty of Medicine, University of Manitoba, Winnipeg, Manitoba, Canada
[4]Departments of Surgery & Family Medicine, Faculty of Medicine, University of Manitoba, Winnipeg, Manitoba, Canada
[5]Manitoba Health, Winnipeg, Manitoba, Canada

Corresponding author:
Yang Cui, Department of Community Health Sciences, Faculty of Medicine, University of Manitoba, Winnipeg, Canada.
Email: umcui@myumanitoba.ca

A readmission predictive model can be used to identify patients who are likely to be at highest risk of readmission and would most likely benefit from this intervention. This study developed and validated a risk prediction model for hospital readmission. A risk prediction model stratifies the risk of future hospital readmission, so that specific interventions can be in place to prevent future readmissions and reduce avoidable medical costs. Being able to accurately predict the risks can help health care providers to focus on case management and reduce the numbers of re-hospitalizations after discharge. In an increasing body of literature, risk prediction models for hospital readmission have drawn more and more attention over recent decades.[6–18] Most of the studies use either retrospective administrative data or patients' clinical data to predict high risk of readmission within 30 days of discharge. The evidence indicates that predictive models may be useful to identify high risk of future hospitalization either in the early intervention, during hospitalization, or at discharge. Moreover, two recent studies in the UK and Australia used administrative data to predict patients at risk of hospital readmission within 12 months of discharge; these models identify patients at risk at hospital readmission reasonably well.[7,8]

The main objectives of this study were to: (1) develop and validate a model for predicting all-cause re-hospitalization within one year of discharge and (2) assess the predictive model performance by using key metrics.

Methods

Data source

The data were obtained from the Population Health Research Data Repository (PHRDR) housed at the Manitoba Centre for Health Policy, University of Manitoba (UM). PHRDR holds records for virtually all contacts with the provincial health care system, including physicians, hospitals, personal care homes, home care and pharmaceutical prescriptions of all registered individuals.[19] PHRDR provides a comprehensive historical collection of administrative, registry, survey and other data on all residents of Manitoba. We used four administrative databases to capture data on all residents in Winnipeg. The hospital abstracts database contains all records of hospital admission, patients' age, gender, diagnosis, length of stay, emergent admission and discharge. The medical services database consists of claims for physician visits in offices, hospitals and outpatient departments. The emergency care database monitors visits to the emergency department. The health registry and census databases include marital status and household income.

Study population

The study population included all patients who were aged 35 and older living in the Winnipeg Health Region and had continuous health care coverage by Manitoba Health who were hospitalized at least once between 2005/2006 and 2008/2009. The study population was selected from the hospital abstracts database from 2003/2004 to 2009/2010. This breadth of data allowed us look at whether (1) a readmission occurred within 12 months after the initial discharge, and (2) the patient used hospital and/or emergency department resources before the start of study period.

Outcome variable

The outcome was all-cause re-hospitalization within 12 months after a discharge. A re-hospitalization was defined as a hospitalization within one year after the initial discharge. Patients who at least have one readmission to hospital after a discharge were included. Hospital readmissions related to pregnancy, childbirth and abortion were excluded. All deaths in hospital during the index admission were also excluded. Discharges occurring in four fiscal years 2005/2006 and 2008/2009 were examined.

Potential risk predictors

A number of studies have identified that some clinical and demographic factors are good predictors for hospital readmission.[6,7,9,16] Therefore, a set of clinical and demographic variables was chosen for this analysis and limited only by their availability on the data source chosen (PHRDR). We were also interested in determining if socioeconomic characteristics are predictive for re-hospitalization, because low socioeconomic status is a known risk factor to predict hospital use. A quintile split of total family income was used to create five socioeconomic groups ranging from most disadvantaged (quintile 1) to most advantaged (quintile 5). The demographic and socioeconomic risk factors at baseline were examined including: age (categorized into four groups: <50, 50–64, 65–80 and >80), gender, marital status and annual household income. The clinical and health care utilization factors were used to examine whether these factors contributed to hospital readmission, including whether the patient had a family physician (yes/no), previous emergent department (ER) visits six month prior to index hospitalization, previous hospitalization in the past two years, index hospital length of stay, overall health care costs, primary diagnosis of index hospital admission according to the 10th version of International Classification of Diseases (ICD-10), discharged disposition (home without support services required/others) and emergent admission (yes/no). We used the Charlson Comorbidity Index (CCI) to predict patient outcomes on hospitalization and mortality. CCI is a well-validated tool used to measure the patient's overall comorbidity at the initial hospitalization, and it contains 19 categories of comorbidity, which are primarily defined using ICD-10-CM diagnoses codes; the higher the score, the more severe the burden of comorbidity.[20]

Statistical methods

The characteristics of the study population were summarized either by percentages for categorical variables or by means and standard deviations for continuous variables. T-tests were used to compare means between patients readmitted and not readmitted, and chi-square tests were used to compare proportions. The results of the multivariable regression model were used to develop a risk prediction score by using a regression coefficient-based scoring method. To generate an integer-based point risk score for each predictor variable, scores were assigned by dividing beta coefficients by the absolute value of the smallest coefficient in the model and rounding to the nearest integer. The overall risk score was calculated by adding each component together.[21,22]

The adequacy of the model was assessed by the c-statistic and diagnostic test. C-statistic is identical to the area under the receiver operating characteristic (ROC) curve for dichotomous outcomes. ROC provides a measure of the model's ability to discriminate between those subjects who experience the outcome of interest versus those who do not. The diagnostic test for logistic regression was used to identify poorly fit or overly influential subjects. Finally, sensitivity, specificity, positive and negative predictive value were used for the model calibration and calculated for cutoff threshold of the predicted risk.

We built a risk prediction model using the 21 risk factors mentioned earlier. A series of bivariate analyses were used to examine the association between each independent variable and the outcome variable. Any bivariate analysis with a p-value $<.20$ was a candidate for the model along with all variables of known clinical importance. We used the Wald statistic to verify the importance of each variable included in the multivariable logistic regression. In addition, any variable not selected for the original multivariable logistic regression model was added back to check if that variable might make an important contribution in the presence of other variables. The likelihood ratio test was used to evaluate successive models. The significant interactions among the variables were checked; the inclusion of an interaction in the final model was based on statistical and practical considerations. Finally, 15 variables were significant predictors and were included to produce the risk score index.

The performance of the predictive model and risk index were evaluated from internal validation. Before starting the analysis, half of all study subjects were randomly selected for the derivation sample and the other half for internal validation. The final predictive model was firstly created on the derivation sample, and then the estimated coefficients were applied to the validation sample.

Data manipulation programming and all statistical analyses were performed using SAS version 9.3. This study was approved by the Health Research Ethics Board at the UM (Ethics reference number: H2011:194). Since the data contain personal health information, Health Information Privacy Committee approval was sought and granted (File number: 2011/2012-13).

Results

During the four-year study period, 123,860 patients were hospitalized in all Winnipeg hospitals. The derivation cohort included 61,924 patients, of whom 20,699 (33.4%) were readmitted to hospital in the year following discharge. For patients having hospital readmission in the derivation cohort, the average readmissions were 1.9 (SD 1.6) times, ranging from 1 time to 27 times. The validation cohort included 61,926 patients, of whom 20,883 (33.7%) were readmitted hospital in the year following discharge. Baseline demographic, socioeconomic, clinical, previous health care utilization and comorbidity characteristics for patients readmitted and not readmitted are presented in Table 1. Demographic and socioeconomic factors with statistically significant differences were age, gender and household income. Patients who had CCI >0 also had significantly higher rates of readmission. Regarding health care utilization characteristics at baseline, readmitted patients had higher rates of not having a family physician (70.4%), higher health care costs (34.8%), more previous hospital admission (14.4%), longer hospital length of stay at index hospitalization (4 days or more) (42.9%) and more than two previous ER visits (8.3%), were discharged to or transferred to continuing care or home setting with support services (18.9%), and were admitted through the ER (30.8%). These differences were statistically significant. In addition, the three most prevalent clinical characteristics among the readmitted patients were: diseases of the digestive system, diseases of the circulatory system, and diseases of the musculoskeletal system and connective tissue. In the validation cohort, patients' characteristics at baseline were very similar to the derivation cohort.

Table 1. Baseline patient characteristics of all-cause hospital readmission in derivation cohort (2005/2006–2008/2009).

Characteristics	Factor	Readmission within 12 months Yes ($N = 20,669$)	No ($N = 41,255$)	p
Age at baseline	(Mean, SD)	63.2 (14.2)	59.2 (13.9)	<.0001
	<50	3257 (15.8%)	9544 (23.1%)	
	50–64	6383 (30.9%)	15,324 (37.1%)	
	65–80	7177 (34.7%)	11,529 (28%)	
	>80	3852 (18.6%)	4858 (11.8%)	
Marital status	Married	14,072 (68.1%)	28,383 (68.8%)	0.07
	Not married or unknown	6597 (31.9%)	12,872 (31.2%)	
Gender	Male	9292 (45%)	17,392 (42.2%)	<.0001
	Female	11,377 (55%)	23,863 (57.8%)	
Household Income	Quintile 1 (most disadvantaged)	4166 (21.1%)	7762 (19.4%)	<.0001
	Quintile 2	3859 (19.5%)	7439 (18.6%)	
	Quintile 3	3947 (20%)	7962 (20%)	
	Quintile 4	3934 (19.9%)	8376 (21%)	
	Quintile 5 (least disadvantaged)	3874 (19.6%)	8379 (21%)	
Had a family physician	Yes	6123 (29.6%)	16,164 (39.2%)	<.0001
	No	14,546 (70.4%)	25,080 (60.8%)	
Previous ER visits (6 months prior to hospital admission)	None	15,319 (74.1%)	33,583 (81.4%)	<.0001
	One	3633 (17.6%)	5547 (13.5%)	
	Two and more	1717 (8.3%)	2125 (5.2%)	
Had previous hospital admission in the last 2 years	Yes	2966 (14.4%)	2627 (6.4%)	<.0001
	No	17,703 (85.6%)	38,628 (93.6%)	
Hospital LOS	≤4 days	11,806 (57.1%)	24,716 (60%)	<.0001
	>4 days	8863 (42.9%)	16,539 (40%)	
Costs[a]	Quartile 1	3544 (17.1%)	11,937 (28.9%)	<.0001
	Quartile 2	4391 (21.2%)	11,090 (26.9%)	
	Quartile 3	5533 (26.8%)	9948 (24.1%)	
	Quartile 4	7201 (34.8%)	8280 (20.1%)	
CCI at admission	0	15,310 (74.1%)	35,358 (85.7%)	<.0001
	>0	5359 (25.9%)	5897 (14.3%)	
Most Responsible Medical diagnosis at index admission (ICD-10)	Diseases of the digestive system	3792 (18.4%)	9785 (23.7%)	<.0001
	Diseases of the circulatory system	3007 (14.6%)	3158 (7.7%)	<.0001
	Diseases of the musculoskeletal system and connective tissue	1439 (7%)	4340 (10.5%)	<.0001
	Diseases of the genitourinary system	1551 (7.5%)	4006 (9.7%)	<.0001
	Factors influencing health status and contact with health services	1574 (7.6%)	3800 (9.2%)	<.0001
	Neoplasms	1862 (9%)	3366 (8.1%)	0.0003
	Diseases of the eye and adnexa	2097 (10.2%)	2416 (5.9%)	<.0001
	Symptoms, signs and abnormal clinical and laboratory findings not elsewhere classified	1233 (6%)	2579 (6.3%)	0.16
	Injury, poisoning, and certain other consequences of external causes	1086 (5.3%)	1880 (4.6%)	0.0001
Discharge disposition	Home (no support service required)	16,768 (81.1%)	38,794 (94%)	<.0001
	Other[b]	3901 (18.9%)	2458 (6%)	

(continued)

Table 1. Continued

Characteristics	Factor	Readmission within 12 months		
		Yes ($N = 20{,}669$)	No ($N = 41{,}255$)	p
Emergent admission	Yes	6365 (30.8%)	7879 (19.1%)	<.0001
	No	14,304 (69.2%)	33,376 (80.9%)	

[a]Including expenses of hospitalization, prescription drugs, medical services and ER visits.
[b]Patients were discharged or transferred to an acute care inpatient institution or continuing care or home setting with support services or left against medical services or others.

The multivariable logistic regression was used in predicting hospital readmissions. The results indicated that several characteristics were strongly associated with readmission. The parameter estimates and odds ratios of the final full model are summarized in Table 2. The significant predictors for re-hospitalizations were: older age, male, disease of the eye and adnexa, disease of the circulatory system, at least one hospital admission in the past two years, disease of the neoplasms, an emergent (index) hospital admission, CCI > 0, disease of the genitourinary, length of stay for the index hospitalization (<4 days), higher overall health care costs, discharge to continuing care or home needing support, not having a family physician, disease of the musculoskeletal system and connective tissue, and having more than two emergency visits in the six months prior to the index hospital admission. The significant interaction was age and gender. Discrimination power in the derivative cohort was acceptable (C statistic = 0.701; 95% CI: 0.696–0.705). The logistic regression diagnostic techniques suggest that no observations seem to be outliers which might have had an extreme impact on the model's coefficients. The standard Pearson residuals which measure the relative deviations between the observed and fitted values are also in the acceptable range (within ± 3), indicating that the model is good.

The results of the multivariable logistic regression analysis were then used to develop a predictive risk scoring system. The risk scores of readmission were quantified according to the magnitude of the association of each of the predictors (Table 2). The total risk score for an individual patient was determined by assigning points for each factor and summing. Consequently, a risk score was generated between −13 and 78 for each patient who has had a reference admission. Patients were stratified into 10 deciles by level of risk, indicating a gradient in the risk for hospital readmission. As can be seen from Figures 2 and 3, in the derivation sample, the predictive and observed were close, especially for low risk patients. In the validation sample, the results were very similar to the derivation set.

Table 2. Risk score system of hospital readmission.

Characteristics	Regression coefficient (β)	Adjusted odds ratio (95% CI)	Risk score
Discharged to:			
Continuing care or home needing support	1.03	2.80 (2.64, 2.97)	21
Home no support service required	Reference		0
Costs:			
>$1,268 (median)	0.41	1.51 (1.46, 1.58)	8
≤$1,268 (median)	Reference		0
Had a family physician:			
Yes	−0.41	0.66 (0.64, 0.69)	−8
No	Reference		0
Diseases of the circulatory (ICD10_chapter9):			
Yes	0.52	1.67 (1.58, 1.78)	10
No	Reference		0
Diseases of the eye and adnexa (ICD10_chapter7):			
Yes	0.81	2.25 (2.11, 2.41)	16
No	Reference		0
Emergency admission:			
Yes	0.34	1.41 (1.34, 1.48)	7
No	Reference		0
Neoplasms (ICD10_chapter2):			
Yes	0.35	1.42 (1.33, 1.52)	7
No	Reference		0
Had previous hospital admission in the last 2 years:			
Yes	0.65	1.91 (1.80, 2.03)	13
No	Reference		0
CCI at admission:			
>0	0.24	1.28 (1.22, 1.34)	5
=0	Reference		0
Diseases of the musculoskeletal system and connective tissue (ICD10_chapter13):			
Yes	−0.16	0.85 (0.80, 0.91)	−3
No	Reference		0

(continued)

Table 2. Continued

Characteristics	Regression coefficient (β)	Adjusted odds ratio (95% CI)	Risk score
Diseases of the genitourinary system (ICD10_chapter14):			
Yes	0.09	1.09 (1.02, 1.17)	2
No	Reference		0
Previous ER visits≥2:			
Yes	0.12	1.12 (1.05, 1.21)	2
No	Reference		0
Hospital LOS:			
≥4 days	−0.05	0.95 (0.92, 0.99)	−1
<4 days	Reference		0
Age<50			
Male	−0.07	0.94 (0.88, 0.99)	−1
Female	Reference		0
Age 50–64			
Male	0.06	1.06 (1.02, 1.10)	1
Female	Reference		0
Age 65–80			
Male	0.19	1.20 (1.16, 1.26)	4
Female	Reference		0
Age 80+			
Male	0.31	1.37 (1.28, 1.47)	6
Female	Reference		0

The performance of the final predictive model was also tested by using sensitivity, specificity, positive and negative predictive values. Sensitivity measures the proportion of persons who are correctly identified to be at risk for re-hospitalization. It provides a measure of how well the risk score performs in identifying cases that are potentially at risk for re-hospitalization and require additional case-management. Specificity measures the proportion of persons who are identified to be not at risk for the re-hospitalization. If the predictive model incorrectly predicts that patients who would not be readmitted to the hospital, it will result in inefficient and costly interventions. Specificity is important to assess the potential cost-effectiveness for the predictive models and the case-management services required for the intervention. Subsequently, proper assignment of persons to intervention should help to better allocate scarce health care resources. Since the distribution of risk score is left-skewed, we used the median as a cutoff threshold. At a median risk score threshold in the derivation cohort, the sensitivity, specificity, positive and negative predictive value were 45.5%, 79%, 68.8% and 58.6%, respectively. Our predictive algorithm has a false positive rate of 21%, indicating these patients who were identified at risk of readmission will not have a subsequent admission.

Discussion

In Canada, there is little research that has examined who is at risk of readmission 12 months after discharge. Similarly, little research has been done to develop and validate a predictive model for hospital readmission within 12 months. This study attempted to fill these gaps in the literature. In the present study, we developed and internally validated a predictive model of all-cause hospital readmission within one year of discharge by using administrative data. This study also explored the capacity of population-based administrative health data to predict hospital readmissions. Our findings suggest that patient demographic characteristics, previous health services utilization and clinical features can be used to estimate the risk of hospital readmission, such as older age, male, diagnoses, comorbidity, length of index hospital stay, previous ER visits, etc. The discrimination of our final model performed moderately well on the ROC curve for predicting hospital readmission. In addition, the model has reasonable accuracy in terms of positive predictive value for future hospitalizations (Figure 1).

This risk predictive model and risk scoring system have important implications for early intervention at discharge and population health planning for developing effective strategies for prevention of readmissions. Because the predictive model can help identify patients who are truly at risk of future hospital readmission, the preventive care from an integrative medical team in a community setting can use such information and provide effective interventions based on a patient's characteristics and disease conditions. Potential health care net savings could be generated from averted downstream inpatient costs. The findings from this study are comparable to two recent studies conducted in other jurisdictions in predicting readmission within 12 months.[7,8] Moreover, our study examined variables associated with the social determinants of health, such as family income and marital status, and health care costs to predict re-hospitalization, which very few models have incorporated.[11]

This study was population-based, which represents the full coverage of hospital readmission cases occurring in the population being studied. We used the Manitoba PHRDR, which is regularly updated and had comprehensive follow-up. Therefore, these data were found to have high accuracy and quality.[23] The findings of this study have limitations that can impact their interpretation. First, information about informal care from family members or friends after discharge and medication reconciliation was not available in the administrative data. Thus, we could not examine such factors although they may be associated with health services use and readmission risk.[24–26] Second, since

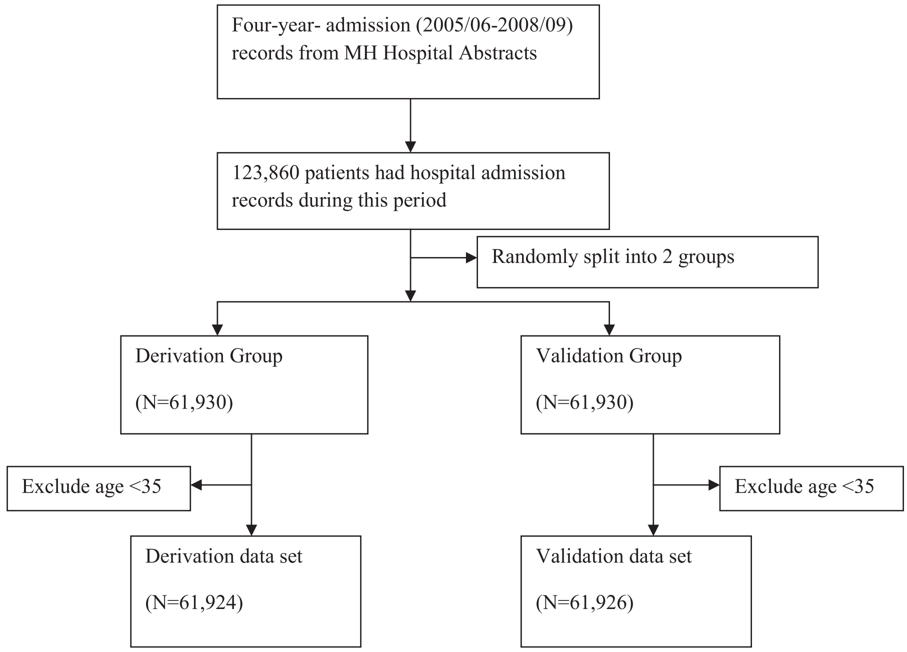

Figure 1. Creation of derivation and validation data sets.

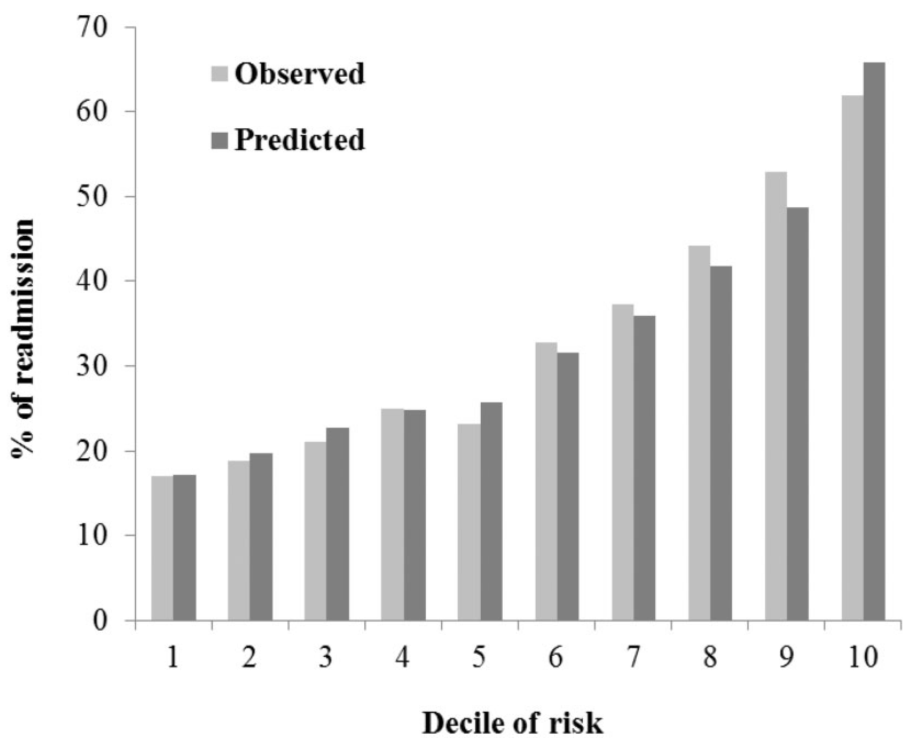

Figure 2. Comparison of observed and predicted probability of readmission in derivation cohort.

patients' historical medical records or reports may be valuable to contribute to prevent the risk of readmission, future research is recommended to incorporate electronic medical record data to assess if the discriminatory power, sensitivity, specificity, positive and negative predictive values of the predictive model can be improved. Third, the results generated from this study may or may not be generalizable. It should be noted that a predictive model developed for one population may not be applicable to other populations;

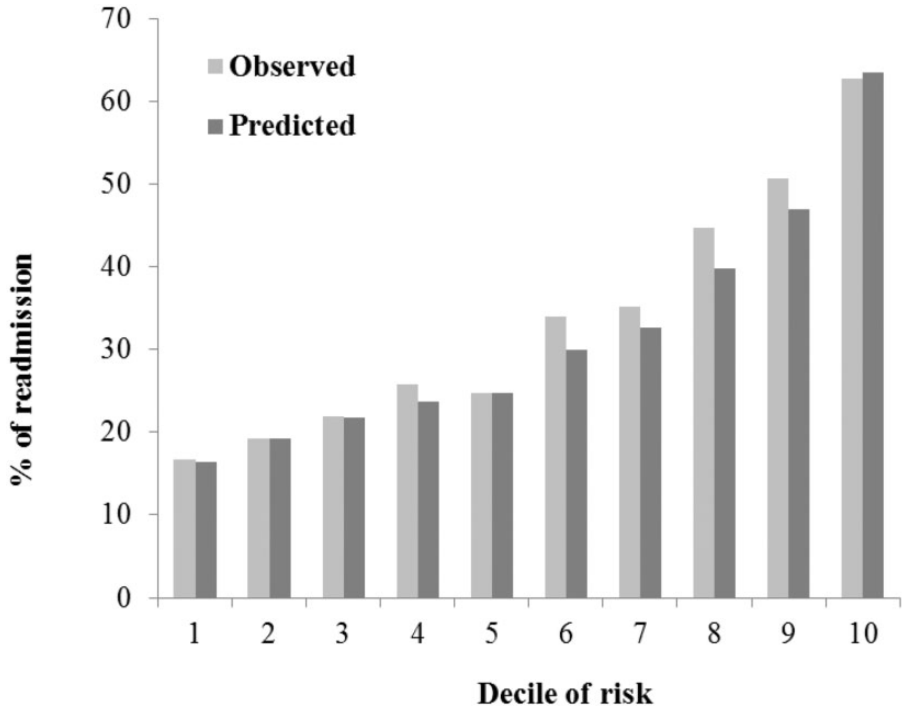

Figure 3. Comparison of observed and predicted probability of readmission in validation cohort.

therefore, further external validation in a variety of settings for this model should be investigated.

In summary, this population-derived risk predictive tool will be useful for health care providers in the Winnipeg Health Region by identifying those individuals most likely to benefit from special transitional services in the community. In addition, the findings yielded from this study will help to improve long-term chronic condition management and ensure the efficient use of health care resources.

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References

1. Canadian Institute for Health Information. *National health expenditure trends, 1975 to 2011*. Canadian Institute for Health Information, Ottawa, Canada, 2011.
2. Monette M. Hospital readmission rates under the microscope. *CMAJ* 2012; 184: E651–E652.
3. Canadian Institute for Health Information. *All-cause readmission to acute care and return to the emergency department*. Canadian Institute for Health Information, Ottawa, Canada, 2012.
4. Minott J. Reducing hospital readmissions. http://www.academyhealth.org/files/publications/Reducing_Hospital_Readmissions.pdf (2008, accessed 9 July 2013).
5. Foster D and Harkness G. Healthcare reform: pending changes to reimbursement for 30-day readmissions. http://www.communitysolutions.com/assets/2012 Institute_Presentations/ acareimbuesementchanges051812.pdf (2010, accessed 9 July 2013).
6. Philbin EF and DiSalvo TG. Prediction of hospital readmission for heart failure: development of a simple risk score based on administrative data. *Rev Port Cardiol* 1999; 18: 855–856.
7. Billings J, Dixon J, Mijanovich T, et al. Case finding for patients at risk of readmission to hospital: development of algorithm to identify high risk patients. *BMJ* 2006; 333: 327.
8. Howell S, Coory M, Martin J, et al. Using routine inpatient data to identify patients at risk of hospital readmission. *BMC Health Serv Res* 2009; 9: 96-6963-9-96.
9. van Walraven C, Dhalla IA, Bell C, et al. Derivation and validation of an index to predict early death or unplanned readmission after discharge from hospital to the community. *CMAJ* 2010; 182: 551–557.
10. Lewis GH. ''Impactibility models'': identifying the subgroup of high-risk patients most amenable to hospital-avoidance programs. *Milbank Q* 2010; 88: 240–255.
11. Kansagara D, Englander H, Salanitro A, et al. Risk prediction models for hospital readmission: a systematic review. *JAMA* 2011; 306: 1688–1698.

12. Gruneir A, Dhalla IA, van Walraven C, et al. Unplanned readmissions after hospital discharge among patients identified as being at high risk for readmission using a validated predictive algorithm. *Open Med* 2011; 5: e104–e111.
13. Billings J, Blunt I, Steventon A, et al. Development of a predictive model to identify inpatients at risk of re-admission within 30 days of discharge (PARR-30). *BMJ Open* 2012; 2: e001667.
14. Billings J, Georghiou T, Blunt I, et al. Choosing a model to predict hospital admission: an observational study of new variants of predictive models for case finding. *BMJ Open* 2013; 3: e003352.
15. Choudhry SA, Li J, Davis D, et al. A public-private partnership develops and externally validates a 30-day hospital readmission risk prediction model. *Online J Public Health Inform* 2013; 5: 219.
16. Shulan M, Gao K and Moore CD. Predicting 30-day all-cause hospital readmissions. *Health Care Manag Sci* 2013; 16: 167–175.
17. Zapatero A, Barba R, Marco J, et al. Predictive model of readmission to internal medicine wards. *Eur J Intern Med* 2012; 23: 451–456.
18. van Walraven C, Wong J and Forster AJ. LACE+ index: extension of a validated index to predict early death or urgent readmission after hospital discharge using administrative data. *Open Med* 2012; 6: e80–e90.
19. Manitoba Centre for Health Policy. Population health research data repository. 2009 http://mchp-appserv.cpe.umanitoba.ca/viewDefinition.php?definitionID=103357 (2009, accessed 19 June 2013).
20. Manitoba Centre for Health Policy. Concept: Charlson Comorbidity Index, http://mchp-appserv.cpe.umanitoba.ca/viewConcept.php?conceptID=1098 (2009, accessed 19 June 2013).
21. Donze J, Aujesky D, Williams D, et al. Potentially avoidable 30-day hospital readmissions in medical patients: derivation and validation of a prediction model. *JAMA Intern Med* 2013; 173: 632–638.
22. Leung GM, Rainer TH, Lau FL, et al. A clinical prediction rule for diagnosing severe acute respiratory syndrome in the emergency department. *Ann Intern Med* 2004; 141: 333–342.
23. Manitoba Centre for Health Policy. MCHP data quality framework. 2014, http://umanitoba.ca/faculties/medicine/units/community_health_sciences/departmental_units/mchp/protocol/media/Data_Quality_Framework.pdf (2014, accessed 17 August 2014).
24. Wolff JL and Kasper JD. Informal caregiver characteristics and subsequent hospitalization outcomes among recipients of care. *Aging Clin Exp Res* 2004; 16: 307–313.
25. Hernandez AF, Greiner MA, Fonarow GC, et al. Relationship between early physician follow-up and 30-day readmission among Medicare beneficiaries hospitalized for heart failure. *JAMA* 2010; 303: 1716–1722.
26. Kripalani S, Jackson AT, Schnipper JL, et al. Promoting effective transitions of care at hospital discharge: a review of key issues for hospitalists. *J Hosp Med* 2007; 2: 314–323.