Roles of Nonclinical and Clinical Data in Prediction of 30-Day Rehospitalization or Death Among Heart Failure Patients

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ABSTRACT

Background: Selecting heart failure (HF) patients for intensive management to reduce readmissions requires effective targeting. However, available prediction scores are only modestly effective. We sought to develop a prediction score for 30-day all-cause rehospitalization or death in HF with the use of nonclinical and clinical data.

Methods and Results: This statewide data linkage included all patients who survived their 1st HF admission (with either reduced or preserved ejection fraction) to a Tasmanian public hospital during 2009−2012. Nonclinical data (n = 1,537; 49.5% men, median age 80 y) included administrative, socioeconomic, and geomapping data. Clinical data before discharge were available from 977 patients. Prediction models were developed and internally and externally validated. Within 30 days of discharge, 390 patients (25.4%) died or were rehospitalized. The nonclinical model (length of hospital stay, age, living alone, discharge during winter, remoteness index, comorbidities, and sex) had fair discrimination (C-statistic 0.66 [95% confidence interval (CI) 0.63−0.69]). Clinical data (blood urea nitrogen, New York Heart Association functional class, albumin, heart rate, respiratory rate, diuretic use, angiotensin-converting enzyme inhibitor use, arrhythmia, and troponin) provided better discrimination (C-statistic 0.72 [95% CI 0.68−0.76]). Combining both data sources best predicted 30-day rehospitalization or death (C-statistic 0.76 [95% CI 0.72−0.80]).

Conclusions: Clinical data are stronger predictors than nonclinical data, but combining both best predicts 30-day rehospitalization or death among HF patients. (*J Cardiac Fail 2015;21:374−381*)

Key Words: Algorithm, cardiac failure, readmission, risk score, quality.

Heart failure (HF) is the leading cause of hospitalization and rehospitalization for adults >65 years of age.[1,2] Although HF hospitalization rates have decreased by nearly 30% during the past decade owing to improvements in medical therapy and management of risk factors,[3] there has been no sign of a reduction in readmission rates after HF hospitalization.[4] High readmission rates after an index HF admission are a problem not only in the United States,[5] but also in other countries and across different racial and ethnic groups.[6,7] Because hospital readmission is costly and usually considered to be preventable,[2] reducing readmission rates has become a national priority to improve health care and to reduce costs. The Centers for Medicare and Medicaid Services initiated public reporting of 30-day readmission rates as an indicator of performance at hospital level, but this has had very minor effects on improvement.[8] Financial penalties have now been established for hospitals in the United States with the highest readmission rates within 30 days after discharge.[9] The impact of HF on Australian society and the national economy are of proportionate magnitude to those in the United States. Although 30,000 Australians are diagnosed with incident HF each year, HF (as either the primary or a contributory diagnosis) accounted for 140,000 admissions on 2008, implying that readmissions account for a significant proportion of the annual HF cost of A$1 billion annually.[10] Actions to prevent HF admission and readmission are as important in Australia as in the United States and elsewhere.

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A number of interventions have been tested by hospitals in efforts to prevent readmissions of HF patients. However, the processes of care in these programs have varied substantially, likely reflecting the uncertainty about what is most effective.[11] Furthermore, most of these interventions have not been associated with lower readmission rates.[11] This may be partly due to failure to target the interventions to patients at high risk of readmission. When applied indiscriminately without regard to the patients' levels of risk, the cost-effectiveness of these interventions may be greatly reduced. Indeed, the few hospitals that reported to have developed successful readmission programs abandoned them very soon after their trials owing to financial constraints.[12] Reliable risk scores to identify HF patients with high risks of short-term readmission or death are therefore needed. Unfortunately, currently available risk scores are only modestly effective.[13,14]

Readmission is an indicator of disease progression and poor outcomes of chronic HF. Data have shown that mortality rates are significantly higher for HF patients with repeated hospitalizations.[15] This highlights the need of identifying patients with high risks of readmission for further interventions to improve post-discharge outcomes, including death. Therefore, in the present study, we aimed to develop a prediction model of 30-day all-cause readmission or death among HF patients with the use of both nonclinical and clinical data.

Materials and Methods

Study Population

This statewide data linkage included all 1,727 HF patients (with either reduced or preserved ejection fraction) who had their 1st admission to a public hospital in Tasmania with HF from July 2009 to June 2012. These patients were identified by their coded diagnoses (International Classification of Diseases, Ninth Revision, Clinical Modification [ICD]: 402.x1, 404.x1, 404.x3, 428.x, and 428.xx). Because this study aimed to evaluate the post-discharge risk of readmission or death, we excluded 190 patients (11.0%) who died during the index hospitalization. Our analyses included the remaining 1,537 patients (49.5% male) who survived the 1st admission.

Primary Outcome

The primary outcome of this study was all-cause rehospitalization or death within 30 days after discharge. Therefore, any patients who were readmitted and/or dead within 30 days of the first discharge were defined as having a positive outcome. Rehospitalization dates were obtained from administrative data from the Clinical Informatics and Business Intelligence Unit of the Department of Health and Human Services of Tasmania. Dates of death were obtained from medical records and the Australian National Death Index.

Nonclinical Data

Nonclinical data included general administrative, socioeconomic, geomapping, and seasonal data. General administrative data (including age, sex, sociodemographic data, residential address, dates of admission and discharge, and number of ICD-coded diagnoses at discharge) were provided by the Clinical Informatics and Business Intelligence Unit of the Department of Health and Human Services of Tasmania and were available for the whole cohort. Socioeconomic status based on residential post code was derived with the use of the Australian Bureau of Statistics Index of Relative Socioeconomic Disadvantage.[16]

Geomapping data based on residential addresses were produced by Esk Mapping and GIS (Australia). Statistical area level 1 (SA1), the 2nd smallest geographic area defined in the Australian Statistical Geography Standard,[17] was used in the majority of the geomapping analyses. The population per SA1, number of persons living in a single household per SA1, number of employed persons per SA1, number of unemployed persons per SA1, and number of persons not in the workforce per SA1 were calculated with the use of data from the Basic Community Profile of the 2011 Census of Population and Housing.[18] Remoteness index based on residential address reflects how far away a geographic area is from service towns of different sizes based on the road distance.[19] For seasonal data, in the southern hemisphere, winter is defined as June to August, spring is defined as September to November, summer is defined as December to February, and autumn is defined as March to May.[20] This information was used to create a binary variable for each season in analyses.

Clinical Data

Clinical data (including medical history, medications, physical measurements, and blood tests) were obtained from medical records and the closest examination before discharge from the first admission and were available from 977 patients. Physical measurements included body weight, blood pressure, heart rate, and respiratory rate. Blood biochemical measurements included troponin I, C-reactive protein, albumin, blood urea nitrogen, creatinine, hematocrit, hemoglobin, and B-type natriuretic peptide. For analytic purposes, troponin I (normal <0.03 μg/L) was dichotomized because this variable was skewed; the other blood biochemical parameters were treated as continuous variables to avoid losing information as well as to estimate their dose-response relationships with the outcome. HF classification was defined with the use of the New York Heart Association (NYHA) functional class.[21] The Charlson comorbidity index was calculated as described elsewhere.[22] Patients were considered to have a history of life-threatening arrhythmia if they had ≥ 1 episode of ventricular tachycardia or fibrillation shortly before or during their 1st hospitalization with HF.

Statistical Analyses

Baseline characteristics of the patients are reported in Table 1 (nonclinical data) and Table 2 (clinical data). In these tables, categoric variables are reported as the number of patients with percentage, and continuous variables are reported as median with interquartile range.

Log-binomial regression was used to estimate the relative risks. Potential predictors of 30-day HF readmission or death were identified by assessment of their potential causation and statistical associations with the outcome. The nonclinical prediction model was developed from Table 1, the clinical model from Table 2, and the combined model from both. Tables 1 and 2 also express the change of deviance (G, the difference between the null deviance and residual deviance), reflecting the improvement of predictive ability of the univariable model compared with the null model