

Short-term adjusted outcomes for heart failure

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ABSTRACT

Purpose: Heart failure (HF) is recognized as a major problem in industrialized countries. Short-term adjusted outcomes are indicators of quality for care process during/after hospitalization. Our aim is to evaluate, for patients with principal diagnosis of HF, in-hospital mortality and 30-day readmissions for all-causes using two different risk adjustment (RA) tools.

Methods and Results: We used data from the hospital discharge abstract (HD) of a retrospective cohort of patients (2002-2007) admitted in Tuscan hospitals, Italy. Considered outcomes were in-hospital mortality and readmission at 30 days. We compared the All-Patients Refined Diagnosis Related Groups (APR-DRG) system and the Elixhauser Index (EI). Logistic regression was performed and models were compared using the C statistic (C). The examined records were 58.202. Crude in-hospital mortality was 9.7%. Thirty-day readmission was 5.1%. The APR-DRG class of risk of death (ROD) was a predictive factor for in-hospital mortality; the APR-DRG class of severity was not significantly associated with 30-day readmissions ($P>0.05$). EI comorbidities which were more strongly associated with outcomes were nonmetastatic cancer for in-hospital mortality (odds ratio, OR 2.25, $P<0.001$), uncomplicated and complicated diabetes for 30-day hospital readmissions (OR 1.20 and 1.34, $P<0.001$). The discriminative abilities for in-hospital mortality were sufficient for both models (C 0.67 for EI, C 0.72 for APR-DRG) while they were low for 30-day readmissions rate (C 0.53 and 0.52).

Conclusions: Age, gender, APR-DRG ROD and some Elixhauser comorbidities are predictive factors of outcomes; only the APR-DRG showed an acceptable ability to predict hospital mortality while none of them was satisfactory in predicting the readmissions within 30 days.

Keywords: Heart failure, In-hospital mortality, Patient readmission, Quality improvement

Introduction

Leading causes of disease burden are noncommunicable diseases such as cardiovascular disease. The number of people dying from this diseases has grown 30% since 1990 (1). Among cardiovascular diseases, heart failure (HF) is now recognized as a major and escalating public health problem in industrialized countries with ageing population (2). Approximately 1-2% of the adult population in developed countries have HF, with a prevalence up to 10% among persons 70 years of age or older (2, 3). There are many causes of HF, and these vary in different parts of the world. Coronary artery disease is

the cause of approximately two-thirds of cases of systolic HF, although hypertension and diabetes are probable contributing factors in many cases (3). Other causes are viral infection (recognized or unrecognized), alcohol abuse, chemotherapy (e.g., doxorubicin) and "idiopathic" dilated cardiomyopathy (3). Considering the high rates of hospitalization for HF and the ongoing treatment and care it requires, its management requires a significant amount of healthcare expenditure in industrialized countries (2), with only the 30-day readmissions cost in the United States approximately \$15 billion, so finding tools to identify patients at risk and to reduce the undesirable outcomes becomes a priority (4). Higher quality care can reduce the risk of adverse outcomes in the short term, as has been shown by several interventions for patients with HF (5). The high risk of death (ROD) or rehospitalization after hospitalization for HF is due to the fact that an hospitalization is often an expression of a state of severe HF (6), the therapies are no longer effective and/or poorly tolerated and only a device or a transplant may improve symptoms (6, 7). The transition between the time in which the patient is followed during hospitalization to the time in which they are followed in the outpatient setting is a critical period because of the severity of disease, the age and the likely comorbidities, and so proper planning of follow-up is required (8). The assessment of

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indicators of negative outcomes, such as in-hospital mortality and 30-day readmissions, can be used to test the quality of care offered; recognizing patients' risk for these outcomes is a clear advantage for the improvement of health services. It is important that comparisons are made using risk adjustment (RA) tools; in fact the RA approach is a valid and useful instrument for quality improvement activities (9), this continues to be used in reports on the quality and efficiency of the hospital, but is now also a frequent input for calculations of health plan, and is used with increasing frequency for measuring and reporting the performance of physicians, networks, groups and even individuals (10). In an increasingly competitive market for hospital services and health, the interest in measuring health outcomes has obviously grown, as they can be used as quality indicators to compare hospitals on outcomes (11-13). The comorbidity measures were developed to predict outcomes most commonly evaluated in research in hospital services—length of stay, charges and in-hospital death (14, 15). These data must be risk-adjusted to create a level-playing field to assess the quality of interventions, regardless of differences attributable to the severity of the disease (10, 16). The ideal tool would adjust for conditions that reflect the patients' severity of illness (SOI) at admission or the natural history of the patients' illness, but not adjusted for complications that could have been averted or ameliorated with optimal medical care (16). The aim of the study is to evaluate, for patients with principal diagnosis of HF, in-hospital mortality and 30-day readmissions for all-cause using two different risk adjustment tools.

Methods

Settings and data selection

We used data from the hospital discharge records (HD) of a retrospective cohort of HF patients (2002-2007) admitted in Tuscany hospitals (central Region of Italy). The inclusion criteria were having the principal diagnosis of HF (ICD9CM: 428x, 398.91, 402.01, 402.11, 404.01, 404.3, 404.11, 404.13, 4047.91, 404.93). Moreover subjects were selected on the basis of absence of other hospitalization in the previous 365 days for the same disease; the major diagnostic categories equal to 5; and age >65 years. We excluded other interventions to the heart and/or vessels and/or valves (ICD9CM = 35.x, 36.x, 37.x), and did not consider resignation from spinal care unit, rehabilitation, long-term care and neuro-rehabilitation. Readmissions between 0 and 1 day after discharge were considered transfers and therefore it was decided to exclude them from the counting of readmission. Moreover the outcomes considered were 1) in-hospital mortality and 2) hospital readmission at 30 days after discharge for all-cause.

Tools

Comorbidity measures are applicable to large administrative dataset, which are now widely available at the national state, health plan, hospital and in some cases physician levels (17, 18). The tools chosen were All-Patients Refined Diagnosis Related Groups (APR-DRG) and Elixhauser Index (EI), based on administrative data. APR-DRG calculates the level of severity and ROD data from the index hospitalization, while

EI calculates on the basis of all admissions of the three previous years. APR-DRG software assigns descriptors to each case on the SOI class and the ROD class (16). The SOI and ROD classes (minor, moderate, major and extreme) are determined separately based on secondary diagnosis and interactions between these diagnoses and age, principal diagnoses and selected procedures (16). The SOI and ROD subclasses moreover describe the impact on the intensity of absorption of resources in the care process (19). The EI tool is based on a set of measures related to the presence of 30 comorbidity diagnoses obtained from the HD and DRG of last three years.

Statistical analysis

Logistic regression models were used to estimate risk-adjusted outcome measures (20); then several significant predictors were incorporated in turn using odds ratio (OR). The performance of the models was assessed by measures of calibration (Hosmer-Lemeshow) and discrimination (area under the ROC curve). Discrimination indicates the ability of the model to predict a higher probability of death for those who actually die rather than to those who remain alive, while the calibration shows how the average of the predicted values conforms to the average of the observed values. The analysis was performed with STATA software 10.0 (Data Analysis and Statistical Software, Copyright 1996-2013 StataCorp LP). Statistical significance was set at $P < 0.05$.

Results

The number of HD studied was 58,202 with 80% of patients 75 years or more. Descriptive analysis and crude OR in-hospital mortality and 30-day readmissions are shown in Table I. Crude mortality was 9.7%, lower in females and increasing with age. The 30-day readmissions was 5.1%, higher for hospitalization longer than 10 days (OR 1.27; $P \leq 0.001$). In-hospital mortality, in the adjusted model, was significantly associated with ROD. At the highest level of ROD, extreme, the likely to die was 35.32 times higher than to the minor level. The moderate level of SOI was significantly associated with 30-day readmissions (OR 1.13; $P = 0.006$). In-hospital mortality with APR-DRG model showed that females are significantly less likely to die in the hospital (OR 0.82; $p < 0.001$) compared to males; increasing age is associated with a higher probability of in-hospital death; OR for ages 75/84 and 85+ years was 1.47 ($P < 0.001$) and 2.72 ($P < 0.001$), respectively (Tab. II). Among patients who are readmitted to the hospital, the SOI is low even in subsequent hospitalizations: 84% of patients had minor or moderate disease severity in both the index hospitalization at first readmission. Among patients with major or extreme severity at index hospitalization, 82% still has minor or moderate severity with readmission (Tab. I). Using EI, comorbidities more strongly associated with outcomes were nonmetastatic cancer (OR 2.25; $P < 0.001$) for in-hospital mortality and uncomplicated and complicated diabetes (OR 1.20; $P < 0.001$ and OR 1.34; $P < 0.001$, respectively) for hospital readmission. Other characteristics associated with both in-hospital mortality and with 30-day readmissions were gender (females are less likely to meet the outcomes) and increasing

TABLE I - Analysis for in-hospital mortality and 30-day readmissions

In-hospital mortality	No of death (%)	Total (%)	OR	[95% Confidence interval]		P value
Age (years)						
65-74	486 (4,3)	11.276 (19,4)	1			
75-84	2.154 (8,0)	26.798 (46,0)	1.94	1.75	2.15	0.001
85+	3.023 (15,0)	20.128 (34,6)	3.92	3.55	4.33	
Gender						
M	2.591 (10,1)	25.641 (44,1)	1			
F	3.072 (9,4)	32.561 (55,9)	0.93	0.88	0.98	0.007
Days						
hospitalization <=10 days	4.410 (9,8)	44.971 (77,3)	1			
hospitalization >10 days	1.253 (9,5)	13.231 (22,7)	0.96	0.90	1.03	0.251
SOI						
Minor	1.280 (6,4)	20.002 (34,4)	1			
Moderate	2.363 (7,4)	32.011 (55,0)	1.17	1.09	1.25	
Major	1.717 (29,7)	5.781 (9,9)	6.18	5.70	6.69	0.001
Extreme	303 (74,3)	408 (0,7)	42.21	33.57	53.07	
ROD						
Minor	316 (2,6)	12.360 (21,2)	1			
Moderate	3.344 (8,7)	38.543 (66,2)	3.62	3.22	4.07	
Major	1.551 (23,8)	6.508 (11,2)	11.92	10.52	13.52	0.001
Extreme	452 (57,1)	791 (1,4)	50.82	42.46	60.82	
30-day readmissions	Readmission at 30 days (%)	Total (%)	OR	[95% Confidence interval]		P value
Age						
65-74	509 (4,6)	10.655 (20,6)	1			
75-84	1.228 (4,8)	24.311 (46,9)	1.06	0.95	1.18	0.056
85+	910 (5,1)	16.817 (32,5)	1.14	1.02	1.27	
Gender						
M	1.223 (5,1)	22.743 (43,9)	1			
F	1.424 (4,7)	29.040 (56,1)	0.91	0.84	0.98	0.015
Length of stay						
≤10 days	1.931 (4,6)	39.967 (77,2)	1			
>10 days	716 (5,7)	11.816 (22,8)	1.27	1.16	1.39	0.001
SOI						
Minor	872 (4,5)	18.467 (35,7)	1			
Moderate	1.563 (5,1)	29.231 (56,4)	1.14	1.05	1.24	
Major	210 (5,0)	3.983 (7,7)	1.12	0.96	1.31	0.010
Extreme	2 (1,9)	102 (0,2)	0,40	0.1	1.64	
ROD						
Minor	475 (3,8)	11.904 (23,0)	1			
Moderate	1.815 (5,0)	34.676 (67,0)	1.33	1.2	1.47	
Major	335 (6,4)	4.871 (9,4)	1.78	1.54	2.05	0.001
Extreme	22 (6,2)	332 (0,6)	1.71	1.1	2.66	

age (Tab. III). APR-DRG showed to have an acceptable discriminative ability on in-hospital mortality (C 0.72) while, the ability was inadequate using EI (0.67). Both APR-DRG and EI showed to have a not satisfactory discriminative ability on 30-day readmissions (APR-DRG C 0.52 and EI C 0.53).

Conclusion

Our study aims to make a contribution to the identification of patients potentially at risk of early death or readmission using tools that are easy and handy in an important field for

TABLE II - Adjusted APR-DRG model for considered outcomes

APR-DRG model	Odds ratio	P	[95% Confidence interval]	
In-hospital mortality				
Gender F	0.82	0.001	0.77	0.86
Cl age 75-84	1.47	0.001	1.32	1.63
Cl age 85+	2.72	0.001	2.43	3.03
ROD moderate	2.34	0.001	2.06	2.65
ROD major	7.89	0.001	6.91	9.01
ROD extreme	35.32	0.001	29.36	42.50
30-day readmissions				
Gender F	0.89	0.006	0.82	0.97
Cl age 75-84	1.07	0.214	0.96	1.19
Cl age 85+	1.17	0.007	1.04	1.31
SOI moderate	1.13	0.006	1.03	1.23
SOI major	1.1	0.229	0.94	1.28

TABLE III - EI model for considered outcomes. Only significant variables are shown

Elixhauser model	Odds ratio	P	[95% Confidence interval]	
In-hospital mortality				
Gender F	0.81	0.001	0.76	0.86
Cl age 75-84	1.95	0.001	1.76	2.16
Cl age 85+	3.96	0.001	3.58	4.39
Hypertension uncomplicated	0.42	0.001	0.38	0.47
Neurological disorders	2.29	0.001	2.01	2.60
Chronic pulmonary disease	0.86	0.001	0.80	0.93
Diabetes uncomplicated	0.84	0.001	0.77	0.92
Diabetes complicated	0.82	0.013	0.70	0.96
Hypothyroidism	0.46	0.001	0.33	0.64
Nonmetastatic cancer	2.25	0.001	1.96	2.58
Blood loss anemia	0.48	0.001	0.36	0.64
Deficiency anemia	0.59	0.001	0.48	0.72
Depression	0.27	0.001	0.17	0.41
30-day readmissions				
Gender F	0.9	0.005	0.82	0.96
Cl age 75-84	1.09	0.121	0.98	1.21
Cl age 85+	1.20	0.001	1.07	1.35
Hypertension uncomplicated	0.83	0.002	0.74	0.93
Diabetes uncomplicated	1.20	0.001	1.08	1.35
Diabetes complicated	1.34	0.001	1.13	1.59
Nonmetastatic cancer	1.24	0.076	0.98	1.58

epidemiology, severity, cost and use of resources such as HF. This analysis showed that for the HF APR-DRG model predictable variables identified are ROD class, age, gender; in contrast EI model identified comorbidities as nonmetastatic cancer and diabetes as predictable factors for considered outcomes. An acceptable ability to predict hospital mortality is shown only for the APR-DRG of the two RA models in patients affected by HF, while for EI the ability to predict in-hospital mortality is a bit less. Readmission at 30 days for all-cause was not successfully predictable with APR-DRG and EI. We can therefore say that both models studied are good predictors for the outcome "in-hospital mortality"; much of the literature has confirmed that the APR-DRG as an RA tool for predicting mortality is adequate (16, 21). The results also show that the risk of hospital readmission is not related to the SOI at admission. This result is not surprising because the readmission at 30 days seems to be related to factors other than the severity of the illness at admission such as higher rates of early follow-up (8); socioeconomic factors are also associated with a higher risk of 30-day readmissions (22). In fact, the complexity of patients with HF, often elderly, with complex medical regimen and with numerous comorbidities, when discharged from hospitals, requires early and enduring follow-ups, regardless of the class of SOI they belong to (8). It is also interesting to note that a multidisciplinary approach (geriatrician cardiologist, dietician, general HF education by nurse, social worker, home visits) to the patient with HF reduces hospital readmissions for all causes (23). Initiatives to improve the quality of care for HF should also go for the establishment of registers on a large scale that include the period from hospitalization to outpatient follow-up to detect and avoid unacceptable intra- and extra-hospital outcomes, and also to better understand the heterogeneous population of patients with HF, so as to guide policy decisions, guidelines and clinical research (7). The literature, moreover, confirms that the methods of risk adjustment are suitable to compare not only the outcomes of different therapeutic and diagnostic procedures but also the results produced by different hospitals. It is also useful to assess the risk of a given outcome that could be produced from a health facility with certain characteristics for patients with certain comorbidities for HF. In particular, it has recently been shown that more comprehensive use of diagnosis identified as present on admission improves the performance of mortality risk adjustment methods, and these improvements meaningfully change the results of hospital mortality rate comparisons (24-29). A limit of this study is that the patients who died after discharge, at home or at a different hospital, were not part of mortality calculation, since the policy of early discharge with transfer to other hospitals often near the residence of the patients is common in Tuscany, a possible bias being present. Moreover the number of readmissions may seem lower than the data reported in the literature; this may be put in relation to the characteristics of inclusion and exclusion of patients in the study. These choices are targeted to exclude patients with specific clinical features and select positively "new" patients for HF. In conclusion we can say that in the comparison between the two models both appear to be adequate with regard to the ROD and may therefore be useful for their intended purpose to measure the severity of the patients; however, the EI makes use of more data, and then gives more information about the patient, and is also a free tool. It is

important to keep looking for risk adjusted instruments able to predict other outcomes of interest for public health and health service, as indeed can be the 30-day readmissions (30). In view of our results, it seems appropriate that the experience with HF can also be tried with other pathological conditions.

Clinical implication

Because the factors that influence the possible rehospitalization are varied, the use of tools, that take data directly from the HD, can be of great importance when predicting the outcomes. These models must be evaluated and compared with each other to be useful to clinicians. Our work fits into that line of study that aims to evaluate these tools for risk stratification in order to provide clinicians with supplemental information for a better evaluation of patients' weighted clinical condition. The adoption of such techniques can be envisaged for a multidimensional approach to patients in recognized risk, to improve the performance of doctors in preventing hospital readmissions and deaths in hospital.

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