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Prediction of Patient Readmission by LACE Index components at Cardiac Care Unit of an Iranian Hospital: A Cohort Study

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A R T I C L E I N F O

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A B S T R A C T

Background: One approach to improve efficiency in health care is to identify patients with high risks of readmission so that resources should be distributed in a way they would benefit targeted care. A model named LACE (length of stay, acuity of admission, Charlson comorbidity index (CCI) , and number of emergency department visits in preceding 6 months) has been proposed to predict patient readmission which is widely used due to its simplicity to rank factors' risks. The aim of this study is to determine if LACE Index could be used to predict Iranian hospital readmission.

Methods: This was a prospective cohort study in which the prediction of readmission for patients admitted to the cardiac intensive care of Shahid Beheshti Hospital of Qom during April to June 2012 within one month after the discharge was evaluated based on 4 items of LACE index. Following-up readmission states by making calls within a month after discharge. Purposive sampling was used to select the sample, patients having four most prevalent chronic heart diseases in the CCU of the hospital were selected and at last sample size was 109 patients. We used logistic regression, the phi and Spearman correlation coefficient to analyze data using $SPSS_{18}$. the significance level was considered as 5% in all tests.

Results: Among the items of LACE model, 48.6% of patients stayed at the hospital for 4 to 6 days. Only 11 patients (10.09%) referred to the hospital after a month. None of the components of the LACE index could enter the stepwise logistic regression model.

Conclusions: Considering that LACE model with its four items is a weak in predicting readmission, in order to improve the model in predicting the readmission of cardiac patients, it is recommended that individual variables and factors associated with the service providers be added to it.

Keywords: Readmission, LACE Index, CCU, Hospital, Iran

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Introduction

Readmissions to hospitals are a major concern for patients, care providers, and hospitals because of their effects on costs and quality of hospital cares and their imposing pressures on patients and their families (1, 2). Around one fifth of patients covered by Medicare are re-hospitalized within 30 days after discharge, which imposes extra costs on health system (3). Medicare Plan assigns 17.4 billion dollars to unplanned readmissions(4). About 73 million dollars has been spent in four states of the US on preventable conditions (5, 6). In fact, unplanned readmissions are the results of low quality or deficits of the system. Due to costly and preventable events of readmission, this is an important issue in system reform and health care policies (6).

Some factors that reduce readmission rates are better predischarge assessment, patient education, postdischarge care, better clinical management and stabilization prior to discharge, adequate outpatient care after discharge, appropriate discharge planning, and provision of resources at home which meet patient's needs (7-9). Readmissions can be prevented by a number of interventions. Such interventions usually include a combination of enhanced discharge planning, postdischarge follow-up and Heart Failure management services(10, 11).

One of the important reasons for the low quality of care is that patients are discharged without having realistic access to follow up in hospitals (12). The attention of payers to reducing the costs of early re-hospitalization and increasing the readmissions within 30 days after discharge has attracted researchers and authorities of health care towards finding solutions to reduce potential and preventable readmissions to hospitals (13-15). One approach to increase efficiency in this sector is to identify patients with high risks of readmission and to distribute resources in a way that they benefit targeted care. It is a significant approach because it causes rare resources to be used where they are most effective with positive results.

Previous studies in Chronic Heart Failure (CHF) showed readmissions might be associated with length of hospitalization, medical comorbidities, frequent Emergency department (ED) revisits, low literacy skills, and severity of illness (16-19). Hospital readmissions have a considerable impact both on hospital expenses and on the functional and psychological condition of patients (20). Also identification help in order to reduce the demand for hospital beds and improve the quality of inpatient care (8). On the other hand, it caused patient care programs are designed and implemented in the way that all required services are provided to patients at the first time of inpatient visit and helps the hospitals supervise them more accurately and to attempt to prevent their readmission for the same disease by more seriously controlling the factors affecting readmission (12, 21).

In recent years, a model named LACE (length of stay, acuity of admission, Charlson comorbidity index (CCI) , and number of emergency department visits in preceding 6 months) has been proposed to predict patient readmission which is widely used due to its simplicity to rank factors' risks. Van Walraven and colleagues (22), proposed this model and the scoring system with logistic regression analysis of patient's characteristics which has been proved to be successful. They investigated the characteristics of 4812 discharged operated or non-operated patients in 11 hospitals of Canada to identify the most important characteristics in predicting patients' characteristics and consequently reached a prediction model now extensively used around the world (23, 24). The present study presents four characteristics of patients to predict unplanned readmission within 30 days after discharge (14, 23, 24). This paper tries to predict the rate of readmissions to cardiac intensive care unit (CCU) in terms of LACE index because CCU is the main unit which admits cardiac patients. It is a special unit of the hospital which provides intensive care and the beds of this unit are occupied by patients suffering from cardiac disorders or problems (25, 26). Results of this paper can be a guideline for hospital medical personnel to identify patients with high risks of readmission and to centralize care services in these groups. It should be noted that, considering the characteristics of Iran's health system, this model has not been used in this country so far, and this paper attempts to investigate this model.

Materials and Methods

This study was a prospective cohort study in which the probability of readmission for patients admitted to the CCU within one month after the discharge of the patient was evaluated. The population consisted of cardiac patients admitted to the CCU of Shahid Beheshti Hospital of Qom, Iran, during three months (April – June 2012). 244 patients were hospitalized during three months in the CUU which had 9 beds. Purposive sampling was used to select the sample, so that among all the patients hospitalized for three months, patients having four most prevalent chronic heart diseases in the CCU of the hospital - including CHF (38 cases), unstable angina (31 cases), pulmonary edema (21 patients) and various types of arrhythmia (19 cases)- were selected as sample. As many studies mentioned that CHF associated with high rates of mortality and morbidity including hospital readmission and is the most common cause for readmission among patients with CHF(27). This is also true about unstable angina(28). So we choose CHF and other prevalent chronic disease in CCU.

Inclusion criteria included to have one of the above four diseases and the patient's desire for a recording of his/her information in the checklist of the study. The researcher provided the patients with sufficient information regarding the research subject and the follow-up procedure, and the patients entered the study with their informed consent. The exclusion criteria was included the patient's having acute cardiac diseases or other cardiac diseases or his/her unwillingness to participate in the study. The number of patients with the above four diseases who were hospitalized in the CCU during this interval and have these criteria for participate in this study was 110. Upon admission, the demographic information (including age, gender, education, etc.) of these patients was filled into the demographic information section of the LACE checklist.

To help remember these four elements, the name 'LACE' was assigned to it. A LACE checklist was used in this paper; it has 4 items: length of stay with a score from 0 to 6 based on the number of the days from 0 to 14, admission type including outpatient or hospitalized with a score of 0 and 3 respectively, comorbidities based in Charlson index with a score of 0 to 6, and finally the number of ER visits with a score of 0 to 4 according to the visit times from 0 to 4. Total score of LACE index was 0 to 19. This model was validated and accepted with one million sample of discharged operated and non-operated patients in all hospitals of Ontario (from 2004 to 2008)and the mean difference between observed and expected patients in readmission rate and death was only 1.6% (from 0.04% to 6.6%). LACE index is a tool used for identification of predictable readmissions (10, 14).

The Chalrson Comorbidity Index is a prognostic Index proposed Mary Charlson et al. (29), in 1987 as a means for quantifying the prognosis of patients enrolled in clinical trials. It is a method of categorizing comorbidities of patients based on the International Classification of Diseases (ICD) diagnosis codes found in administrative data, such as hospital discharge abstracts data. Each comorbidity category has an associated weight, based on the adjusted risk of mortality or resource use, and the sum of all the weights results in a single comorbidity score for a patient. A score of zero indicates that no comorbidities were found. The higher the score, the more likely the predicted outcome will result in mortality or higher resource use.

The score of each patient in each of the components of the LACE index was determined as follows: the patient's hospitalization length was determined by the nurse upon the patient's discharge, the type of admission and existence of comorbidity was determined upon admission to the unit and in initial evaluation of the patient by the nurse and also the data extracted from the patient's records, the number of times of referring to the emergency department during the previous 6 months based on the data extracted from the patient's record and asking the patient and his/her family upon admission to the unit, and all were recorded in the LACE index checklist.

One month after the patients' discharge, the researcher followed up their condition by phone. The patients were asked if they have refereed to that hospital or other hospitals on account of that disease. If the answer was affirmative, date, reason, and length of hospitalization would be asked and recorded in the related form. Only unplanned referring was considered as readmission, and patients who had referred to the hospital during the previous month with prior appointment for angiography and angioplasty were not included in the readmission numbers.

The validity of the information obtained from the patients was confirmed by one of their family members by phone. To confirm the validity data obtained from the patients and their families, having obtained written authorization form the presidents of the hospitals, the researcher investigated the hospitalization information of the sample in the HIS systems of the hospitals equipped with CCU so as to find out whether the patients have been readmitted within one month after their discharge. Thus, the authenticity of the predicted probability was investigated by LACE index.

The objective of the present study is to predict patient's readmission by the components of the LACE index. To determine how there is a linear relationship between of binary response variable (readmission and no readmission) and independent variables of Length of Stay (LOS), admission type, comorbidity diseases and the number of referring to the emergency department, logistic regression was used. To investigate the correlation between independent variables with regard to the type of variables, the phi and Spearman correlation coefficient were used. Tests were analyzed using $SPSS_{18}$, and the significance level was considered as 5% in all tests.

In addition, the declaration of Helsinki was considered for ethical issues.

Results

Follow up one patient (out of 110 patients) was failed because the patient did not answer the follow-up phone call and therefore, the patient's information was deleted from the final data. There were no deaths during follow-up.

The greatest number of patients (73.4%) was in the above 50-years-old group and the smallest number (2.8%) was in the 21-30-years-old group. 54% of the patients were female and 46% were male. Among LACE items, 48.6 % of patients (the highest number) stayed at the hospital for 4 to 6 days and 0.9% (the lowest number) stayed for one day. 84% of the patients had acute admission and 16 % were outpatients. 54.1% of patients (the highest number) suffered from comorbidity diseases of diabetes, cerebrovascular and peripheral diseases, digestive diseases or heart failure (second group of Charlson index) and 0.9% (the lowest number) were in the fourth group namely connective tissue disease. 83.5% of the patients in the last six months had four or more visits to ED and 3.7% of them (the lowest amount) visited the ED only two times. Only 10% of patients revisited the hospital after a month. LACE index mean and standard deviation are 11.5 and 1.93 respectively for all of sample patients.

In this study, stepwise logistic regression (forward conditional in $SPSS_{18}$) was used to predict patient admission with the components of LACE index. Based on $SPSS_{18}$ software default, Entry and Removal Probabilities are considered 0.05 and 0.10 respectively. None of the components of the LACE index could enter the model. To report the Beta coefficients, all the components entered the model simultaneously using the default (enter) method (Table 3). Since the frequency of some cohorts is low and causes a substantial increase in estimate deviation, some cohorts combined with one another; Of course this combination has no impact on significance. Spearman's and Cramer's V correlation coefficient was used to investigate the correlation of independent variables considering the type of variable being investigated. The correlation between some of the components of LACE index was statistically significant. Based on the results, there was a relationship between the number of ED visits prior six months and the type of their admission. Besides, the between the number of ED visits prior six months is not independent of the length of their stay in the hospital.

The values obtained from table 4 indicate that there is no high correlation between investigated variables. But, the existence of some correlations was confirmed. For example, individuals with more length of hospitalization had more references to emergency departments. Using the results obtained from these two tests, the relationship between the response variable and predictor variables, as well as a relationship among independent variables can be observed.

Based on the statistical tests conducted, no linear relationship was detected between the components of LACE index and patient readmission, and components of this index is unable to predict patient readmission. Perhaps, by discovering a relationship- not necessarily linear- it may be possible to predict patient readmission.

Table 1. Demographic characteristics of the sample

Demographic variables		Frequency (%)
Age	Under 30	3 (2.7)
	Between 30 and 40	5 (4.6)
	Between 40 and 50	21 (19.3)
	Over 50	80 (73.4)
Gender	Male	50 (45.9)
	Female	59 (54.1)
Education	Under diploma	94 (86.2)
	Diploma	9 (8.2)
	Associate's degree	1 (1)
	Bachelor's degree	2 (1.8)
	Master's degree	2 (1.8)
	PhD	1 (1)
Disease	Chronic heart failure (CHF)	38 (34.9)
	Unstable angina	31 (28.4)
	Pulmonary edema	21 (19.3)
	Various types of arrhythmia	19 (17.4)

Table 2. Components of LACE index according to readmission

Components of LACE index	Frequency (%) Readmission	No readmission	Total
Length of stay in hospital less than 1 day	0	0	0
1 days	0	1 (1)	1 (0.9)
2 days	0	5 (5.1)	5 (4.6)
3 days	0	16 (16.3)	16 (14.7)
4-6 days	7 (63.6)	46 (46.9)	53 (48.6)
7-13 days	4 (36.4)	26 (26.5)	30 (27.5)
14 and more days	0	4 (4.1)	4 (3.7)
Type of admission ambulatory	1 (9.1)	17 (17.3)	18 (45.9)
Acute and hospitalization	10 (9.1)	81 (82.7)	91 (54.1)
Comorbidity No former history	2 (18.2)	17 (17.3)	19 (17.4)
Myocardial infarction (MI) - mellitus diabetes - brain vessels diseases, brain vascular diseases, gastrointestinal diseases	8 (72.7)	51 (52)	59 (54.1)
Liver diseases- mellitus diabetes accompanied by risks of end organs- congestive heart failure- obstructive pulmonary disease-lukemia-lymphoma-cancer-acute renal diseases	1 (1.9)	29 (29.6)	30 (27.5)
Connective tissue diseases	0	1 (1)	1 (1)
Acute renal diseases, acquired immune deficiency syndrome (HIV/AIDS), infection	0	0	0
Metastatic cancer	0	0	0
Number of times of referral to emergency department within the previous six month without an appointment	0	0	0
Once	0	0	0
Twice	0	4 (4.1)	4 (3.7)
Three times	1 (9.1)	13 (13.3)	14 (12.8)
Four times or more	10 (90.9)	81 (82.7)	91 (83.5)

Table 3. Result of fitting logistic regression for readmission prediction

Components of LACE index		Estimate (ß)	Standard Error	Odds ratio	P
Length of stay		0.481	0.48	1.62	0.32
Type of admission	Ambulatory admission	-0.38	1.12	0.68	0.73
	Acute and hospitalization		Reference group		
Comorbidity	No history	1.26	1.27	3.53	0.32
	MI- diabetes - brain vessels diseases, gastrointestinal diseases	1.66	1.10	5.25	0.13
	Liver diseases- mellitus diabetes accompanied by risks of end organs- congestive heart failure- obstructive pulmonary disease-lukemia-lymphoma-cancer-acute renal diseases		Reference group		
number of ED visits prior six months	2 or 36 times	-0.03	1.38	0.97	0.98
	4 times or more		Reference group		
Constant		-5.44	2.49	0.004	0.029

Table 4. Correlation coefficient and P-value of independent variables

Variable	Length of stay	Type of admission	Comorbidity	number of ER visits prior six months
Length of stay	1			
Type of admission	0.19	1		
P	0.51			
Comorbidity	0.387	0.17	1	
P	0.36	0.35		
number of ER visits prior six months	0.65	0.201	0.22	1
P	0.001<	0.03	0.48	

Discussion

No significant relationship was attested in this study between age and readmission. In similar studies, patients above 60 (6, 30), and patients between 41 and 60 (2) were readmitted more frequently to hospitals. Also, no significant relationship was seen between gender and readmission. Ahmadpur (5), and Gou et al .(31), have shown that readmissions are more frequent among males than females. In terms of the first criteria of the readmission LACE index, namely the length of stay at hospital, results showed that most of the patients stayed between 4 and 6 days. Length of stay showed no significant relationship with readmission and the score for this was 5.56 days in average in a study performed by Tazhibi et al (13).

Most patients were readmitted to or hospitalized in acute care in the present study. This can be attributed to the fact that the patients whose cardiac conditions are acute and need intensive care have indications for hospitalization in CCU. There was also no significant relationship between readmission type and readmission. Jenny's study showed that most patients with readmissions were admitted to or hospitalized in acute care in their first admissions (1).

Most patients (54.1%) in this study were in the second group of Charlson index (diabetes mellitus, cerebrovascular and peripheral diseases, digestive disease, and heart failure). There was also no significant relationship between comorbid diseases and readmission. There was no evidence of the relationship between the number of ED visits in the last six month and the intensity of cardiac diseases in similar studies.

The rate of readmission after one month was 10% which was 13.2% in Pearson's study (32). In Gruneir's study, 12.6% of patients were readmitted to hospital one month after discharge (33). Van Walravan got 8% in his study for 4812 patients (22). Jencks indicated that 19.6% or one fifth of patients were readmitted to hospital a month after discharge (4).

Wang et al. (34), demonstrated that The LACE index may not accurately predict unplanned readmissions within 30 days from hospital discharge in CHF patients (34). Cotter et al. argued that the LACE index is a poor tool for predicting 30-day readmission in older UK inpatients. The absence of a simple predictive model may limit the benefit of readmission avoidance strategies (10).

In this study, considering that LACE model with its four defined items is a weak in predicting readmission, in order to improve the model in predicting the readmission of cardiac patients, it is recommended that individual variables and factors associated with the service providers be added to it, too. If LACE index is tested in a greater population, it is possible that a better response be obtained and by enriching its indices, more comprehensive indices are provided for predicting readmission of patients with cardiovascular disease.

There are some possible confounding points. The patients in this study (cardiac patients) who referred to the hospital for hospitalization may also refer for other invasive or non-invasive diagnostic and therapeutic procedures after the last hospitalization (such as PTCA, diagnostic and therapeutic angiography, heart scan, CABG, etc). Such visits are due to the nature of cardiac diseases which intensify gradually and oblige patients to refer to hospitals for diagnosis and therapy; therefore it could have no relation with how services are provided during the last hospitalization, and despite the full attention of medical staff and provision of the finest therapeutic services during the hospitalization, a patient with a high risk of readmission in the next 30 days in terms of LACE index may be readmitted for complementary treatments reasons and not necessarily because of the treatments in his or her last hospitalization.

Some heart problems like low Ejection Fraction or cardiomyopathy make patients susceptible to readmission shortly after the last hospitalization. It is possible that readmissions happen not because of the services provided during hospitalization but because of not following doctor’s orders and lack of sufficient care for the patients at home after getting discharged. Not taking medications on time, insufficient care for the patients by the family, ignorance of patients’ external changes, and not visiting a doctor in the case of identifying symptoms may increase the risk of patient readmission. Misdiagnosis of symptoms and their necessary treatment by the physician prevents the patients from receiving appropriate treatment during their hospitalization and causes them to face problems shortly after discharge and to revisit the hospital.

Because of a cyclic visiting system of cardiac patients by cardiovascular specialists in Qom hospitals’ CCU (all patients are visited each day by one of the specialists not by a specialists chosen by the patient), each patient is visited by different doctors during hospitalization and it is probable that paying attention to certain symptoms and ordering certain medication or other factors lead to conflict of preferences and opinions among specialists which may subsequently make the patient susceptible to return to the hospital shortly after discharge.

Conclusion

The present study is among the first ones conducted in Iran which are in line with predicting the readmission of cardiac patients within 30 days after their discharge; therefore, the findings of the present study will be applicable for policymakers of health sector in the form of the following cases:

- Since heart problems is one of the three common causes of mortality in Iran and the world, and readmission of cardiac patients in hospitals increases the risk of acquiring of hospitals infection and patients' worsening; in consequence, policymakers should encourage more studies on investigating factors affecting the readmission of cardiac patients to identify its common reasons through different studies and evaluate the probability of readmission of cardiac patients by synthesizing them with the LACE model and localizing them for Iran's hospitals.
- Presenting clinical practice guidelines regarding the mode of providing special care for patients who have the possibility of returning to the hospitals within little period after their discharge based on the predicting readmission model.
- On the admission of patients in the related ward, physicians issue the required pharmaceutical care instructions to prevent the occurrence of this phenomenon by estimating readmission probability of patients. In addition, nurses take necessary cares so that patients receive their own required services in the first admission.
- Hospital managers can do reform measures for improving quality in hospitals by extracting the data related to the indices of readmission and investigating its causes and process over time and also using localized model of predicting readmission as well as matching predicting with the reality of readmission.

Limitation of this study was related to gathering data that it was solved by university communication.

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Conflicts of interest

The authors declared that they had no competing interests.

Authors' contributions

Etemadi M, Ebraze A, and Khorasani E designed research; Etemadi M and Khorasani E conducted research; Vaziri Nasab H analyzed data; and Etemadi M, Khorasani E and Vaziri Nasab H wrote the paper. Etemadi M had primary responsibility for final content. All authors read and approved the final manuscript.

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