ISSN: 0975-3583,0976-2833 VOL13, ISSUE 02, 2022

Mortality Prediction Model in Hospital Outcome Evaluation: A Contribution to Assess Effectiveness of Care in Cardiac Care Unit

Anil Kumar Pandey[1]

[1]Medical Superintendent, SIMS, Hapur, Uttar Pradesh, India.

Abstract

Background: To assess the feasibility of Age, risk factors in patients' profileand risks of therapeutic procedures as predictors for a mortality prediction model. **Material and Methods:**Design- Mortality prediction Model was developed by stepwise logistic regression in two stages. First model included risk factors in the patient's profile and second model included significant variables identified by first stepwise regression as also the variables of treatment and procedures. Both were recalibrated by shrinkage method and validated by bootstrapping. Calibration and discrimination were assessed by Hosmer–Lemeshow goodness-of-fit statistics, Briers score and AUROC. Setting:-Hospital in Saudi Arabia. Participants werepatients admitted in cardiac unit from Nov 2011 to Oct 2012, n=2025.**Results:**Overall mortality in hospitalized patients was 2.7%. First stage of model development selected ten variables with p value <.05 i.e. Age, Myocardial Infarction, Ventricular Arrythmia, Mitral Regurgitation, Left Ventricular Failure, Dilated-cardiomyopathy, Cardiogenic-Shock, Renal-failure, New Cerebrovascular Accident and Infection. Hosmer-Lemeshow statistics was 3.81 with a probability of .13. Briers score was .0227 and C statistics was .77. The final model included Age, Infection, CS, NCVA, Cardioversion, HD, Mechanical ventilation and First PCI Intervention. Hosmer-Lemeshow statistics was 7.39 with a p value of .68, Briers score .0210 and C statistics .86 indicating perfect fit. Bootstrappingvalidated the modelwith variables except infection being significant at p value of <.05.**Conclusion:**Considering thattime and cost barriers prevent use of physiology-based mortality model, locally customized model can help in improving effectiveness of care.

Keywords: Prediction model, Effectiveness of care.

Corresponding Author: Anil Kumar Pandey, Medical Superintendent, SIMS, Hapur, Uttar Pradesh, India.

Introduction

The outcome prediction model is an epidemiological tool for clinical research, audit and benchmarking.[1]Prediction modelshave their application in many health care settings includingidentification of patients at high risk for surgery, forecasting physiological status of patients, decision making for allocation of resources, prediction of mortality and so on. In modeling mortality, the model needs to address basic causes underlying the variation in mortality rate. This variation has three sources: the underlying average risk the hospital patients carry on admission; the underlying average effectiveness of care the hospital renders; and unpredictable or chance variation in the risk that individual patients carry, the effectiveness of the care they receive, and the outcome they receive.[2] A model may address last factors causing variation in mortality. Model development has either relied on a theoretical approach in selection and weighing of variables or an empirical approach contrasting the characteristics of survivors and non-survivors in deciding which variables to include in prediction of mortality.[3] The commonly used predictor variables include age, comorbidities, physiological abnormalities, acute diagnosis and lead time bias,[4] though models do not all use the same variables nor collect and process the data similarly to capture

ISSN: 0975-3583,0976-2833 VOL13, ISSUE 02, 2022

these influences. Current published risk prediction models for use in adult intensive care are Acute Physiology and Chronic Health Evaluation (APACHE)II,[5] APACHE III,[6] APACHE IV[7](Simplified Acute Physiology Score (SAPS)II and Mortality Probability Models (MPM)II.[8,9] Apart from their heavy data requirement, and mostly proprietary nature, these models face a few problems with regards to results obtained. Among thembeing the problem of validityof calibration whenapplied to patients care settings in countries other than the countries of origin,[10] developed as they are in North America and Europe,deterioration of performance due to change in case mix and improvements in supportive care etc.[11] Despite the availability of complex Prediction models, these have not been utilized in a systemic manner in developing countries other than for research purpose mostly on account of absence of electronically available data. Moreover, highly specialized ICU's, such as transplant units, or hospitals serving as major referral centers that receive specialized I CU patients would not find Physiology based Models able to accurately estimate the probability of hospital mortality for their ICU patients. It might be unreasonable to assume that Physiology based model developed on and intended for use in general medical-surgical ICUs would work in specialized settings.[12] While the preferred approach to outcome modeling relies on collection of clinical data to provide accurate risk adjustment, absence of electronic medical records makes it difficult. In a study on use of Administrative data in CABG risk model, the model predicted inpatient mortality on par with most clinical risk models used for public reporting.[13] In developing countries development of Prediction model based on Administrative data with information on severity of measures is the only choice till sophisticated method of clinical data collection are adopted. Studies on Prediction model for Independent units like CCU are almost nonexistent. Hence, a study with age, risk factors in patient profile and risk of therapeutic procedures as predictors was planned in a predictive model to make prediction of mortality.

Material and Methods

Study population

Retrospective analysis of concurrent data collected from Daily Administrative Recordof admitted patients for 2025 consecutive patients who were admitted in a cardiac care unit including a 11 bedded coronary care Unit of Saudi Hospital between01 Nov, 2011 and30 Oct2012.Prediction model included death as dependentvariable,defined as death during the stay of patients in the hospital andindependent variablesmeasuring severity of illness, those that characterized the risk factors in the patient's profileand treatment procedures.These includedemographic risksofAge and Sex, binaryrisk factors defining the morbiditiesin the patients and risk of treatment procedures. Commonly occurring morbidities in cardiac patients admitted in the hospital were identified for the purpose of modeling. These included Myocardial Infarction(MI), Acute coronary syndrome (ACS),Unstable Angina(UA),ST Elevation, Ant MI, Inf MI, Post MI, Cardiogenic shock(CS), Arrythmia (Arryth) like Atrial Arrythmia, Ventricular Arrythmia, Complete Heart Block,RBBB&LBBB, Aortic stenosis, Tricuspid stenosis, Pulmonary stenosis, Mitral stenosis, Aortic Regurgitation, Mitral regurgitation, Tricuspid regurgitation, Congestive heart failure (CHF), Left ventricular Dysfunction, Left ventricular failure, Constrictive Cadiomyopathy, Dilated cardiomyopathy, Ischaemic cardiomyopathy, Ejection Fraction (EF),Acute Pulmonary embolism (APE),Ischaemic heart disease(IHD),Two vessel disease(TVD),Three vessel disease (THVD),Diabetes mellitus(DM),Bronchial asthma (BA), Renal failure (RF) creatinine value> 2mg/100 ml, Cerebrovascular accident(CVA),New Cerebrovascular accident(NCVA),Lung diseases such as Pneumonia and COPD andInfection. Infection was recorded when Gram staining and cultures were confirmatory. The risks of Treatment proceduresincludedall procedures performed in the unit such as Primary Percutaneous intervention(PPCI),PCI

ISSN: 0975-3583,0976-2833 VOL13, ISSUE 02, 2022

intervention Ist time (PCII)I and second intervention(PCIII) respectively, Coronary angiography, Plain Old BalloonAngioplasty (POBA), Intraaortic balloon Pump insertion, Temporary Pace making, Cardiorespiratory resuscitationwith chest compression, defibrillation and cardiac message, Cardioversion forrestoration of anycardiac rhythm including resuscitation, Aggrasat (Tirobifan, GP IIb/IIIAReceptor antagonist), Intubation for Artificial ventilation, Thalium scanning, Colour Doppler, Tracheostomy and Haemodialysis.

Data collection

Data were collected from Daily Administrative report generated by supervisory nursing and Administrative Staff for all patients, other than surgical, admitted in a 45 bedded cardiac unitincluding a 11 bedded coronarycare unit, a Day care cath unit, a 05 bedded step-down unit and o5 beddedcardiac surgery ICU in a Multispecialty hospital inSaudi Arabia. The report had details of each patients including therapeutic procedures performed.

Statistical analysis

A univariate regression analysisof all independentvariables was done with dependent variable to identify the association between them. The potential for multiple collinearity was tested using the variance inflation factor, where VIF <10 are desirable.[14] Hospitalmortality was modeled usinglogistic regression. Modeldevelopment occurredin two stages.First stage included a step wiselogistic regression with all independent risk factors in the patients profilewhich hadan odd of >1 and a p value of < .05 in the univariate analysis. In the second stage, a Second forwardstep wise logistic regressionincluded the important variables identified by firststepwise regression andthevariables pertaining to risk oftreatment procedures. To correctthebias in small data set with relatively many parameters, regressionparameterswererecalibrated using shrinkage, a statistical approach to cause flattening of the plot of(predicted, observed) away from the 45° line to deal with overfitting.[15] Shrinkage was achieved by means of penalized maximum likelihood using firthlogit command of stata.[16] A model's predictive accuracy consists of two aspects. First, a prediction should be reliable or calibrated with predicted probabilities matching observed probabilities. The second aspect of predictive accuracy, and perhaps the more important, is discrimination. The discrimination of prognostic modelis the ability to separate patients with good and poor outcomes.[17] Briers Score Hosmer-Lemeshow (HL) statistic were used to measures calibration of the logistic Predictor Selection Model.[18-21] Briers score assesses the mean probability score by calculating mean square error between prediction and observed outcome, and its derivativesassess the decomposition of briers score.For sensible models, Brier scoreranges from 0 (perfect) to .25(worthless).The HL statisticsestablishes "deciles ofrisk " and compares the observed number of persons who have the outcome with an estimatedexpected number of person for each decile to generate X^2statistics for error rate. The distributional properties of X^2 have never been studied but is often compared to a chi-square with degrees of freedom equal to 10-(p+1). Obviously, if (p+1)>10 then more groups would have to be used.A large p-value indicates a good match whereas a small p –value indicates a poor match. Model discrimination was measured by area under the receiver operating characteristics,[22,23] C –statistics. A C –statistics of .7-.8 is considered adequate and a C –statistics of .8-.9 is regarded as very good.[24]A Predictive model also needs validationas performance of a predictive model is overestimatedwhen simply determined on the sample of subjects that was used to construct the model.There are a hierarchy of increasingly stringent validation strategies:

1. internal –procedures restricted to a single data set
2. temporal Validation- evaluation of second data set from the same centre(s)

ISSN: 0975-3583,0976-2833 VOL13, ISSUE 02, 2022

3. external-evaluation on data from one or more other centre (s), perhaps bydifferent investigators.[25]

Internal validity is best estimated with bootstrapping.[26] Bootstrapping replicates the process of sample generation from an underlying population by drawing sample with replacement from the original data set. Model was internally validated using Jackknife bootstrap with 100 replications.[27] In the Jackknife method, sometimes called the "one –left-out" method, one patient is removed and the equation is derived and used on the excluded patient. The patient's predicted state is compared with the true state. This process is repeated many times to determine the standard error.

All statistical analysis was conducted using the Statistical program, Stata-12 for a level of significance of 0.05 and a confidence interval (CI) of 95%. The association measure used was the Coefficients and odds ratio.

Results

In the entire sample of 2025 non-surgical patients admitted in the Cardiac unit, the mortality rate was 2.7%. The distribution of age in percentage was 0-20yrs -1.17%, 20-40 yrs - 11.93%, 40-60yrs - 46.53% and more than 60 yrs - 39.80 %. The percentage of male was 69.7 and female 30.3. Mean Length of stay was 2.8 days with a standard deviation of 2.237 days and Median was 2 days. There was a total of 55 deaths in the period of study. Results of univariate and bivariate analysis with P values <.05 are shown in [Table1].

The variables other than Arrythmia and Atrial had Variance inflation factor between 1 to 1.7. Arrythmia and Atrial had VIF of 5.7 and 4.8. First stage of model development began with a forward stepwise logistic regressionof risk factors in the patient's profile alone as identified significant by univariate and bivariate analysis and selected 10 variables with p value <.05. These included Age, MI, Ventarrhythmia, MR LVF DCMP CS Renal failure NCVA &Infection. Interactions were not significant. [Table 2] shows the Logistic regression coefficients, their confidence interval, standard errors, Z and p.

A penalized regression was then performed. Estimated "mean change in Y per unit of X", slope of coefficientswas smaller with reduced standard errors for all but four variables i. e. CS LVF DCMP MR. Model calibration as measuredas by Hosmer-Lemeshow and Briers score indicated that model was fit, there beingno statistically significant difference betweenobserved and expected value developed through Model. HL Chi2(6) statistics was 3.81 with a probability of 13 Briers score was 0227.The details of statistics are given in [Table3].Model discrimination assessed through C statistics, area under the curve was .7748. Validation of Model through Bootstrapping with penalized regression found that all variables were significant at p value of <.05. Bootstrap standard errors were smaller except for variables, Cardiogenic shock and DCMP. The results of penalized regressionand bootstrap regression with values of mean change in Y per unit of X", coefficients of selected variables in the model are shown in [Table 3].

Calibration plot of First Model [Figure 1] displays a solid line representing the relationship between Actual probability, Lowess (locally weighted scatter plot smoothing) smoothed (28), and Predicted probability. Predicted risks are lower than actual probability. Lowess fits each observation (x i, y i) to a separate linear regression line based on adjacent observation. These points are weighted so that the farther away x value is from x I, less effect it has on determining the estimate of Yi.

Second stage of model development Included a stepwise forward logit regression of dependent variable on all independent variableswhich were part of model one and the additional significant risk factors of therapeutic procedures from Bivariate analysis, subsequent penalized regression and finally internal calibration through bootstrapping. The significant variables included Age. Infection, CS, NCVA, Cardioversion, HD, Mechanical

ISSN: 0975-3583,0976-2833 VOL13, ISSUE 02, 2022

ventilation and First PCI Intervention. Results of stepwise regression are shown in [Table 4].Estimated coefficients of Penalised regression were smaller except for Cardiogenic shock and NCVA with reduced standard errors in all but forCS. HL Chi2(8) statistics was 7.39 with a Probability of0.6880.Briers score was 0.0210.The details of statistics is given in [Table3].Model discrimination assessed through C statistics,area under the curve was .8673. Bootstrapping with penalized regressionvalidated the model with all variables other than infection being significant at p value of <.05.The variable of infection may be non-significant with p value of Infection. o83,Z value of 1.73 on account of strict requirement of infection being recorded only if culture results were positive. Bootstrap standard errors were smaller except for variables, Cardiogenic shock and Infection. The results of penalized regression and bootstrap regression with values of coefficients of selected variables in the model are shown in [Table 5].Calibration plot of Second Model[Figure 2] displays a solid line representing the relationship between Actual probability(Lowess smoothed and Predicted probability. Predicted risks are higher than actual probability but the margin of error is lower than First model. The Final model better performed with c statistics of .8673(0.81729-0.91739) compared to First model with c statistic of .7748(0.70286-0.84681).The Pseudo R^2 was.2978 compared to 0.1839 of first model. [Figure 3] displays comparison of AUROC of two models.

Table 1 Univariate and bivariate analysis between dependent variable Death and independent variables with Odds ration>1 and P value >.05.

	Odds Ratio	**Std. Err.**	**Z**	**P>|z|**	**[95% Conf. Interval]**	**Pseudo R2**	**LR chi2(1)**	**Prob > chi2**
Age	1.04	0.01	4.80	0.000	(1.02-1.06)	0.04	24.67	0.0000
MI	2.04	0.56	2.57	0.010	(1.18 - 3.52)	0.01	6.25	0.0124
CS	12.19	6.48	4.70	0.000	(4.29-34.59)	0.02	14.26	0.0002
Arryth	2.37	0.72	2.85	0.004	(1.30 -4.30)	0.01	7.13	0.0076
Atrial	1.97	0.68	1.98	0.048	(1.00 -3.88)	0.006	3.42	0.0643
Vent	5.86	2.93	3.53	0.000	(2.19 -15.64)	0.01	8.58	0.0034
CHB	2.88	1.55	1.97	0.049	(1.00 -8.28)	0.005	3.00	0.0830
MR	3.17	1.54	2.37	0.018	(1.22 - 8.25)	0.008	4.31	0.0380
LVF	4.54	1.82	3.77	0.000	(2.07 -9.97)	0.02	10.48	0.0012
DCMP	2.99	1.07	3.04	0.002	(1.47-6.06)	0.01	7.43	0.0064
EF	1.06	0.02	2.66	0.008	(1.01 -1.11)	0.009	4.94	0.0263
APE	3.13	1.69	2.12	0.034	(1.08-9.02)	0.006	3.41	0.0648
Renalfailure	5.53	1.96	4.82	0.000	(2.76 - 11.09)	0.03	17.10	0.0000
NCVA |	9.08	10.23	1.96	0.050	(.99-82.67)	0.004	2.44	0.1183
Lungdis	4.60	3.51	2.00	0.045	(1.03-20.52)	0.005	2.79	0.0951
PCII	0.29	0.15	-2.33	0.020	(0.10-0.82)	0.005	7.59	0.0059
IABP	23.74	11.09	6.78	0.000	(9.50-59.31)	0.06	30.69	0.0000
CPR	16.53	6.95	6.67	0.000	(7.25 - 37.70)	0.05	29.45	0.0000
Cardioversion	22.59	8.71	8.08	0.000	(10.60 -48.11)	0.08	44.48	0.0000
Intubation	33.83	10.54	11.30	0.000	(18.36-62.33)	0.19	98.28	0.0000
Tracheostomy	37.07	37.43	3.58	0.000	(5.12 - 268.22)	0.01	9.05	0.0026
Infection	24.48	14.39	5.44	0.000	(7.73- 77.49)	0.03	19.58	0.0000
HD	23.75	11.82	6.37	0.000	(8.96 - 62.99)	0.05	26.94	0.0000

ISSN: 0975-3583,0976-2833 VOL13, ISSUE 02, 2022

Table 2: First model, logistic regression,coefficients, their confidence interval,standard errors, Z and p-values.

Variables	Coefficients	Std Error	Z	P>|z|	[95% Conf. Interval]
Infection	2.79	0.67	4.14	0.000	(1.47- 4.11)
Renalfailure	1.36	0.39	3.47	0.001	(0.59- 2.13)
CS	2.23	0.58	3.84	0.000	(1.07 -3.37)
Age	0.03	0.01	3.76	0.000	(0.01-.06)
LVF	1.17	0.45	2.58	0.010	(0.28 - 2.07)
MI	0.92	0.32	2.82	0.005	(0.28 - 1.57)
DCMP	1.03	0.41	2.49	0.013	(0.22 - 1.84)
MR	1.15	0.53	2.16	0.031	(0.10 - 2.20)
VentArrhythmia	1.22	0.62	1.96	0.050	(0.001-2.44)
Constant	-7.00	0.73	-9.51	0.000	(-8.45 --5.56)
NCVA	2.41	1.01	2.39	0.017	(0.43-4.39)

Table 3: First Model, results of penalized Logistic regression coefficients, bootstrap regression coefficients, their confidence interval, standard errors, Z and p values.

Variables	Coefficients[95 % Conf. Interval]	Std Error	Z	P>|z|	Bootstrap Coefficients[95 % Conf. Interval]	b_Std Error	Z	P>|z|
Infection	2.77 (1.51- 4.04)	0.64	4.31	0.000	2.77(1.53-4.02)	0.63	4.37	0.000
Renal failure	1.34 (0.59- 2.10)	0.38	3.49	0.000	1.34 (0.59-2.09)	0.38	3.50	0.000
CS	2.24 (1.14- 3.34)	0.56	4.01	0.000	2.24 (1.11-3.37)	0.57	3.90	0.000
Age	.039 (0.01-0.05)	0.01	3.70	0.000	0.039 (0.020 -0.05)	0.009	4.17	0.000
LVF	1.18 (0.32- 2.05)	0.44	2.69	0.007	1.18 (.40-1.97)	0.40	2.96	0.003
MI	0.92 (0.29- 1.55)	0.32	2.86	0.004	0.92 (0.29-1.54)	0.31	2.89	0.004
DCMP	1.07 (0.28- 1.86)	0.40	2.67	0.008	1.07 (.22-1.92)	0.43	2.48	0.013
MR	1.22 (0.22- 2.23)	0.51	2.39	0.017	1.22(.23-2.21)	0.50	2.43	0.015
VentArrhythmia	1.29 (0.12- 2.46)	0.59	2.16	0.031	1.29(.23-2.35)	0.54	. 2.39	0.017
NCVA	2.41 (0.43- 4.39)	1.01	2.39	0.017	2.41 (.43-4.39)	1.01	2.39	0.017
Constant	-6.91 (-8.35 - -6.48)	-0.73	-9.47	0.000	-6.91 (-8.10—5.73)	0.60	-11.45	0.000

ISSN: 0975-3583,0976-2833 VOL13, ISSUE 02, 2022

Table 4: Results of Final model, logistic regression, coefficients, their confidence interval, standard errors, Z and p values.

Variables	Coefficients	Std Error	Z	P>|z|	[95% Conf. Interval]
Infection	1.98	0.84	2.34	0.019	(0.324 - 3.64)
CS	2.04	0.65	3.11	0.002	(0.75 -3.33)
Age	0.04	0.01	3.86	0.000	(0.02 - .06)
NCVA	2.75	1.16	2.38	0.017	(0.48-5.03)
Cardioversion	1.17	0.53	2.19	0.029	(0.12 - 2.23)
HD	1.98	0.67	2.95	0.003	(.66 - 3.31)
MechanicalVentilation	2.60	0.38	6.76	0.000	(1.84 - 3.35)
PCII	-1.67	0.70	-2.36	0.018	(-3.06 -.28)
Constant	-6.80	0.78	-8.70	0.000	(-8.33 -5.27)

Table 5: Results of Final Model, penalized Logistic regression coefficients, bootstrap regression coefficients, their confidence interval, standard errors, Z andp values.

Variables	Coefficients	Std Error	Z	P>|z|	Bootstrap Coefficients[95% Conf. Interval]	b_Std Error	Z	P>|z|
Infection	1.99 (.34-3.64)	0.84	2.37	0.018	1.99 (-.26-4.25)	1.15	1.73	0.083
CS	2.08 (.82-3.33)	0.63	3.25	0.001	2.08 (.69-3.46)	0.70	2.95	0.003
Age	0.04 (0.02-0.06)	0.01	3.82	0.000	.04 (.02-.06)	0.01	4.19	0.000
NCVA	2.98 (1.03-4.92)	0.99	3.01	0.003	2.98 (1.18-4.78)	0.91	3.25	0.001
Cardioversion	1.15 (0.12-2.19)	0.52	2.19	0.029	1.15 (.13-2.18)	0.52	2.22	0.026
HD	1.95 (0.65-3.25)	0.66	2.94	0.003	1.95 (.74-3.17)	0.61	3.15	0.002
Mechanical Ventilation	2.54 (1.80-3.28)	0.37	6.73	0.000	2.54 (1.83-3.26)	0.36	6.99	0.000
PCII	-1.53 (-2.58--0.20)	0.67	-2.27	0.023	-1.53 (-2.78- -.277)	0.63	-2.39	0.017
constant	-6.68 (-8.20--5.17	0.77	-8.67	0.000	-6.68 (-8.15- -5.22)	0.74	-8.97	0.000

ISSN: 0975-3583,0976-2833 VOL13, ISSUE 02, 2022

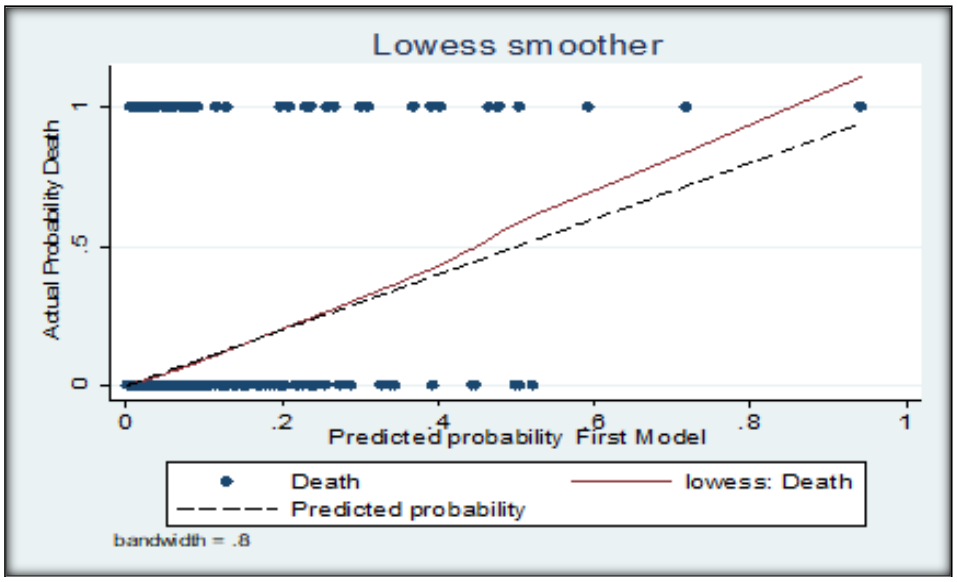

Figure 1: Comparison of actual probability(LOWESS) and predicted probability of death from Model 1.

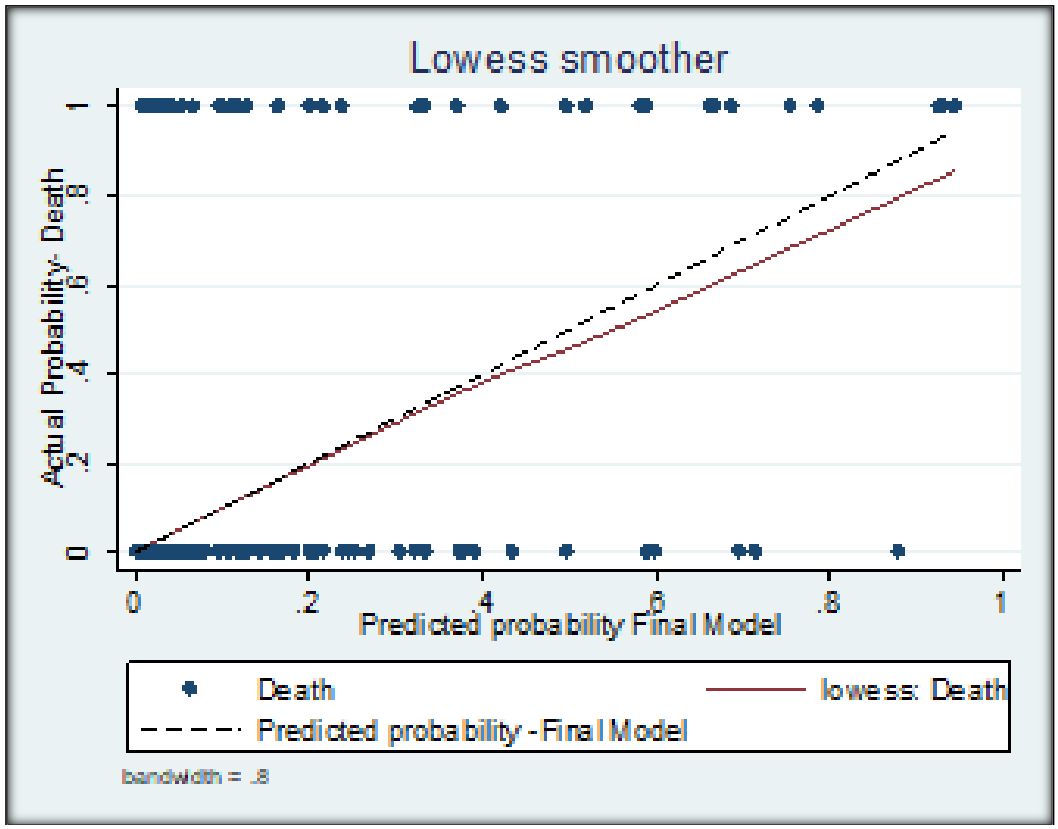

Figure 2: Comparison of actual probability (LOWESS) and predicted probability of death from Model 2

ISSN: 0975-3583,0976-2833 VOL13, ISSUE 02, 2022

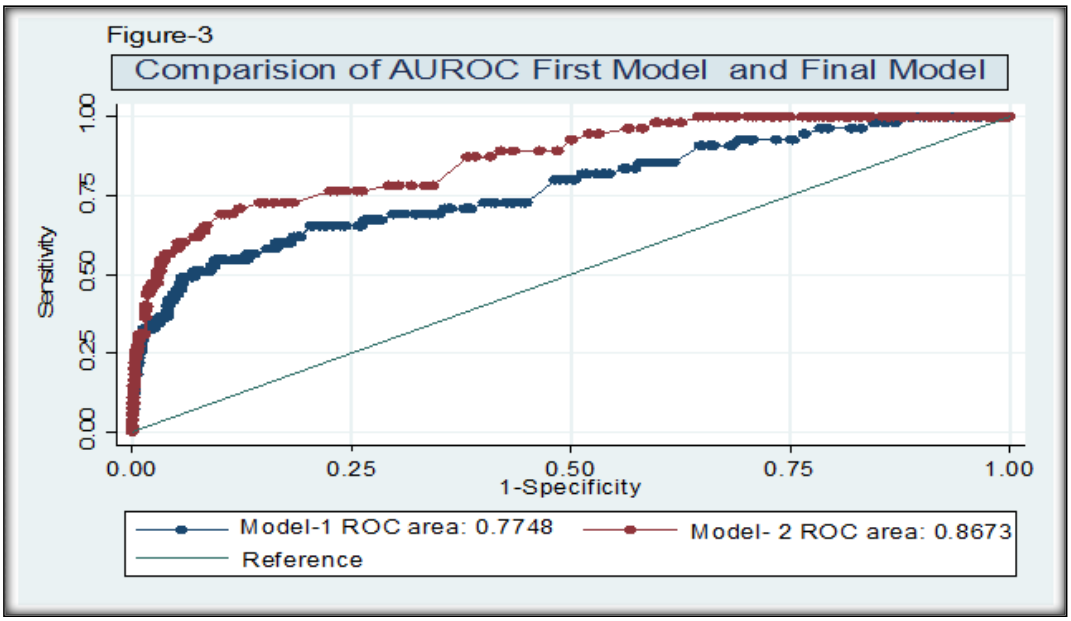

Figure 3: comparison of AUROC of First Model and Final Model.

Discussion

The current study addressed several factors in the patient's morbidity profile, treatment factors as well as in their interactions in a cardiac unit. The purpose of the study was to identify the risk factors associated with short term mortality during patients stay in the hospital and to use them in a prediction model as benchmark for prognostic purpose and to improve effectiveness of care. The model through monitoring over time allows assessment of care in a cardiology unit in the backdrop of Health care system in a developing country. Identification of risk factors for model was based on the reasonableness of risk factors for predicting mortality in a cardiac unit. Off the shelf classification like Charlson et al and Elixhauser et al arenot suitable for cardiology unit.[29,30]

The First model, with binary risk factors alone in the patients profile contributed to aPseudo R^2of only0.1839 compared to 0.2978 in Final Model, and AUROC of 77.48 versus 86.73.The final model did not have structural risk factors like valvular heart disease, congestive heart failure, cadiomyopathies, regurgitation of valve, coronary blockagesignificantly relatedto mortality. Physiological abnormalities other than cardiogenic shock like arrhythmias were also not significant in the final model. These results are in alignment with previous studies that using risk factors in the patient's profile alone has a limited ability to discriminate between hospital survivors and non-survivors.[31,32] Treatment factors likeHemodialysis, DC shock, PCI Ist procedure and mechanical ventilation were significant. The adverse effect of mechanical ventilation has been documented in Mortality prediction Model.[33] However, it is worth mentioning that "non-significant risk factors "in the results should not be interpreted as "no value" but only those significant variables perform better with regards to prognostication in Mortality prediction model. Use of modern technology and better trained staff has,over a period of timein last fewdecades, witnessed better outcomes. It is likely thatin couple of years from now, with better control over care processes, development and implementationnewer and better protocols of treatment and possibly more advanced technology in instrumentation, the picture with regard to some of the significant risk particularly treatment factors may change.

Limitation of the study were many like relatively small number of cases, non-distinguishing ofbaseline conditions (i.e., baseline comorbiditiespresent at the time of admission) from complications arising during a hospital stay, absence of physiological variableswith

ISSN: 0975-3583,0976-2833 VOL13, ISSUE 02, 2022

prognostic value in the prediction model, inclusion of variables with no prior use in literature, non-inclusion of information on admission urgency etc.[34] However, to draw conclusion about quality of care based on severity adjusted outcome will leave out the mortality due to poor monitoring and care. For the research question about the relative importance of predictors, there is no reason to expect that findings may differ by how the risk factors were assessed temporarily. Nonetheless, obvious limitations do not detract from overall conclusion about relative importance of risk factors in the prediction of mortality and their use in benchmarking and monitoring of outcome in a cardiac care unit with a possible role to focus on underlying care processes to bring about improvement in quality of care.

Conclusion

In conclusion, Institutional assessment of performance of cardiology units at aggregate level is desirable to improve performance. Considering thattime and cost barriers preventwidespread use ofphysiology based mortality model, locally customized modelforprediction ofshort mortality in hospital can help inimprovingeffectiveness of care through performance benchmarking and monitoring ofvariables included in prediction model.

References

1. Duke J G, Piercy M, Digiantomasso D, Green VJ. Comparison of intensive care outcome prediction models based on admission scores with those based on 24-hour data. Anaesth Intensive care 2008; 36:845-849.
2. Jencks Stephen F,Daley Jennifer ,David Draper et al. Interpreting hospital mortality data: The role of clinical risk adjustment. JAMA 1988; 260:3611-3616.
3. RowanKathryn M,KerrJohn H ,Major ED et al. Intensive Care Society's Acute Physiology and chronic Health Evaluation (APACHE II) study in Britain and Ireland: A prospective ,multicentre, cohort study comparing two methods for predicting outcome for adult intensive care patients. Critical Care Med 1994; 22:9:1392-1401.
4. Keegan Mark T, Gajic O,Afessa B .Severity of illness scoring systems in the intensive care unit. Critical Care Med 2011; 39:163-169.
5. Knaus WA,Draper EA,Wagner DP ,et al. APACHE II A severity of disease classification system Crit Care Med 1985;13:818-829.
6. Knaus WA,Draper EA,Wagner DP ,et al. The APACHE III prognostic system risk prediction of Hospital mortality for critically ill hospitalized adults. Chest 1991; 100:1619-1636.
7. Zimmerman JE,Krammer AA,McNair DS, Malila FM. AcutePhysiology and chronic Health Evaluation (APACHE IV):hospital Mortality assessment for today's critically ill patients. Crit Care Med 2006; 34:1297-1310.
8. Le Gall Jr,Lemeshow S,Saulnier F. A new simplified acute physiology score (SAPS II) based on a European/North American multicentre study. JAMA 1993; 270:2957 -2963.
9. Lemeshaw S,Teres D Klar J et al. Mortality probability models(MPMII) based on international cohort of intensive care unit patients. JAMA 1993;270 :2478-2486.
10. Harrision David A,Brady Anthony R Parry Green J et al. Recalibration of risk prediction models in a large multicentre cohorts of admissions to adult, general critical care units in the United Kingdom. Crit Care Med 2006; 34:1378-1388
11. Mann SL ,Marsall MR, Woodford BJ et al .Predictive performance of Acute Physiological and Chronic Heath Evaluation releases II ti iV :a single New Zealand centre experience. Anaesth Intensive care2012; 40:479-489.
12. Filkins Robyn L Murphy,Teres Daniel ,Lameshaw Stanley ,Hosmer David W .Effect of changing mix on the performance of an intensive care unit severity –of –illness model:

ISSN: 0975-3583,0976-2833 VOL13, ISSUE 02, 2022

How to distinguish a general from a speciality intensive care unit. Crit care Med 1996; 24:1968-1973.
13. Parker Joseph P,LI ZhongminDamberg Cheryl L et al. AdministrativeVersus Clinical Data for Coronary Artery Bypass Graft Surgery Report Cards The view from California .Med Care 2006;44:687-695.
14. Stevens James P. Applied Multivariate Statistics for the Social Sciences. New York, Taylor & Francis.2009.
15. Harrel Jr Frank E, LEE Kerry L,Mark Daniel B.Tutorial in biostatistics. Multivariable prognostic models:Issues in developing models,evaluating assumptions and adequacy, and measuring and reducing errors.
16. Heinze George, Schemper Michel. A solution to the problem of separation in logistic regression. Statist Med 2002; 21:2409-2419.
17. Harrell Frank E, Lee Kerry L,Payor David B et al. Regression Modelling Strategies for improved Prognostic Prediction. Statistics in Medicine.1984;3:143-152.
18. Brier GW.Verification of forecasts expressed in terms of probability. Monthly Weather Review 1950; 75:1-3
19. Yates JF. External correspondence: Decompositions of the mean probability score. Organ Behav Hum Perform 1982; 30:132-156.
20. Spiegelhalter DJ. Probabilistic prediction in patient management and clinical trials. Stat Med 1986; 5:421-433.
21. Lemeshow Stanley, HosmerJr David W.A review of Goodness of fit statistics for use in the development of Logistic regression Model. Am J Epidemiol 1982; 115:92-106.
22. Hanley JA, McNeil BJ. The meaning and use of the area under a receiver operating characteristic (ROC) curve. Radiology 1982; 143:29-36.
23. Erdreich S Linda, Lee Elisa T. Use of Relative operating characteristic analysis in Epidemiology,a method for dealing with subjective judgement. Am J Epidemiol 1981; 114:649-662.
24. Hosmer D,Lemeshow S.Applied logistic regression.Ist ed. New York: John Wiley & Sons;1989.
25. Altman Douglas G, Royston Patrick. What do we mean by validating a prognostic model? .Statist Med 2000;19:453-473.
26. Streyerberg EW ,Harrel FE Jr, BorsboomGJ ,Eijkemans MJet al .Internal validation of predictive models: efficiency of some procedures for logistic regression analysis. J Clin Epidemiol 2001;54(8):774-81.
27. Efron B. Bootstrap methods: another look at the jackknife. Ann stat 1979; 7:1-26.
28. Cleveland William S.Robust locally weighted regression and smoothing scatterplots. Journal of the American Statistical Association 1979; 74:829-836.
29. Charlson ME, Pompei P,Ales KL, et al.A new method of classifying prognostic comorbidity in longitudinal studies :development and validation .Chronic Dis.1987;40:373-383.
30. Elixhauser A, Steiner,Harris DR, et al :Comorbidity measures for use with administrative data. Med Care.1998;36:8-27.
31. Ho KM, Finn J, Kunaiman Webb SAR. Combining multiple comorbidities with Acute physiology score to predict hospital mortality of critically ill patients:a linked data cohort study. Anaesthesia 2007; 62:1095-1100.
32. Walraven Carl Van, Austin Peter C, Jennings Alison et al. A modification of Elixhauser comorbidity Measures into a point system for hospital death using administrative data. Med Care 2009; 47:626-633. 33.Lemeshow S,Teres D, Klar J,et al: Mortality Probability Model(MPMII) based on an international cohort of intensive care unit patients. JAMA 1993;270:2478-2486.

ISSN: 0975-3583,0976-2833 VOL13, ISSUE 02, 2022

33. Escobar GJ, Greene JD, Scheirer P et al: Risk –adjusting hospital inpatient mortality using automated inpatient, outpatient and laboratory databases. Med Care .2008;46:232-239.