Clinical Prediction Rule for Patient Outcome after In-Hospital CPR

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Abstract

Background: Physicians and patients frequently overestimate likelihood of survival after in-hospital cardiopulmonary resuscitation (CPR). Discussions and decisions around resuscitation after in-hospital cardiopulmonary arrest often take place without adequate or accurate information.

Methods: We conducted a retrospective chart review of 470 instances of resuscitation after in-hospital cardiopulmonary arrest. Individuals were randomly assigned to a derivation cohort and a validation cohort. Logistic Regression and Linear Discriminant Analysis were used to perform multivariate analysis of the data. The resultant best performing rule was converted to a weighted integer tool and thresholds of survival and non-survival were determined with an attempt to optimize sensitivity and specificity for survival.

Results: A 10-feature rule, using thresholds for survival and non-survival, was created; the sensitivity of the rule on the validation cohort was 42.7%, and specificity was 82.4%.

Conclusions: Utilizing information easily obtainable on admission, our clinical prediction tool, the Dartmouth Score, provides physicians individualized information about their patients' probability of survival after in-hospital cardiopulmonary arrest. The Dartmouth Score may become a useful addition to medical expertise and clinical judgment in evaluating and communicating an individual's probability of survival after in-hospital cardiopulmonary arrest after it is validated by other cohorts. Methodologically, because LDA outperformed LR in the creation of this clinical prediction rule, it may be an approach for others to more frequently consider when performing similar analysis.

Keywords: In-hospital CPR; Clinical prediction rul; Cardiopulmonary resuscitation

Introduction

Cardiopulmonary Resuscitation (CPR) was introduced in 1960 to revive victims of acute insult in otherwise good physiological condition [1]. In the past fifty years, CPR evolved from unorganized actions by untrained staff to synchronized teamwork, and has become a fundamental part of medical care for all hospitalized patients in cardiac arrest. Despite these changes, survival from CPR to hospital discharge declined from 24% in 1961 to 14% in 1981 [2]. Since 2000, the national average of survival from in-hospital cardiac arrest to hospital discharge has remained around 18% [3].

In the 1980s, responding to demands for patient autonomy, many hospitals began instituting "Do Not Resuscitate" (DNR) policies allowing patients or their families to determine that no resuscitation be attempted in the event of a cardiac arrest. However, less than 25% of seriously ill patients discuss preferences for resuscitation with their physicians [4-6]. Less than 50% of in-patients who prefer not to receive CPR have DNR orders written [7-9]. A known obstacle to the conversation is physician reluctance to discuss the issue [10,11].

Despite being asked to predict the future frequently by patients, most physicians avoid prognostication, largely because they believe they do not have sufficient information to estimate outcomes [12]. When physicians do engage in this conversation, they overestimate the likelihood of survival to hospital discharge after in-hospital CPR by as much as 300%, and they predict a success rate that is twice that actually observed [13]. This optimism strongly influences the choices of their patients. Accurate information about the probability of survival to discharge after CPR significantly alters patients' DNR preferences [14,15] and might be helpful to patients and their physicians in deciding whether to forego this intervention.

A tool, or clinical prediction rule, utilizing pre-arrest data to estimate an individual's risk of not surviving CPR, could empower physicians to prognosticate more accurately, increase frequency of code status discussions and thereby promote patient autonomy. In the late 1980s and early 1990s, three morbidity scores, Pre-Arrest Morbidity score (PAM) [16,19], Prognosis After Resuscitation score (PAR) [20], and Modified PAM Index (MPI) [21] attempted to predict survival after resuscitation based on univariate meta-analysis (PAR), literature review (MPI) or stepwise logistic regression (PAM). However, changes in CPR algorithms, a changing and ageing population and advances in medical science in the past twenty years have led to a need to update these tools. In addition, advances in the use of computational sciences allow increasingly sophisticated multivariate and multidimensional analysis of data.

Since the creation of the “Utstein template” defining variables and outcomes essential for documenting in-hospital cardiac arrest, it has were excluded due to insufficient data. Independence or dependence with ADLs were removed after analysis revealed that the act of assessing ADL status, not the status itself, was predictive of survival. Using the derivation cohort, a search over all possible 10-feature combinations of the 26 features (approximately 5.3 million combinations) was performed. Each set of 10-features was evaluated by performing 1000 splits of the derivation cohort into a training set containing 90% of the patients in the cohort and a testing set containing the remaining 10%. For each split, LDA was used to generate significance weights for each feature and a temporary threshold was chosen to identify all survivors on the training set. The choice to identify all survivors compromised sensitivity but resulted in a desired low false-positive rate. The average performance over the 1000 randomly chosen test sets was used as a criterion to rank each set of 10 features.

The best performing 10-feature rule was identified and normalized to create an integer classifier with all feature weights falling between 0 and 5 (inclusive). To increase the usability and adaptability of the tool by the healthcare team, all initially negative weights were converted to positive weights by replacing each feature with a negative weight with an equivalent 'absent' feature with the same weight magnitude, albeit positive (e.g., angina pectoris had an initial weight of -4, so we added a feature "no angina pectoris" with a weight of +4). This weight inversion required that the thresholds be shifted by an equivalent amount. The final thresholds reported in this study (≤7 and ≥9) were manually selected. Patients with a score of 7 or lower are likely to survive to discharge, patients with a score of 9 or above are not likely to survive to discharge, and no prediction is made for patients who score between the thresholds. The performance of this rule was evaluated against the validation cohort and the results were compared against other clinical prediction rules.

We also considered the technique of LR. The entire dataset was analyzed with the logistic regression functions as implemented in the statistical computing software R [27]. The binomial logit model was used and calculations took four Fisher Scoring iterations. Four features were identified with p-values less than 0.05. The classifier was normalized to integer weights and thresholds were manually selected to optimize sensitivity and specificity. Since the data was not divided into derivation and validation cohorts, the performance of LR was judged using the entire dataset. Given that we are trying to optimize specificity, it is most fair to compare the LDA model to an LR model with threshold chosen to approximately match the specificity of the LDA-derived rule.

Results

Characteristics of the study population

A total of 470 individual attempts at CPR after cardiopulmonary arrest were reviewed. Overall, 25.7% survived to hospital discharge. In the derivation cohort, the mean age was 67.2 years (Standard Deviation, 14.8 years); 58.5% were men; and 85 of 330 or 25.8% survived to hospital discharge. In the validation cohort, the mean age was 67.0 (Standard Deviation, 15.7 years); 51.4% were men; and 36 of 140 or 25.7% survived to hospital discharge. No significant differences in baseline characteristics between the two cohorts were observed (Table 1).

	Number of Patients		**% of Patients**			
Characteristic	**Derivation Cohort**	**Validation Cohort**	**Derivation Cohort**	**Validation Cohort**	**P-Value**	**Chi-Square Score**
Male Sex	193	72	58%	51%	0.158	1.99
Age >70	148	67	45%	48%	0.549	0.359
Independent ADLs	160	76	48%	54%	0.25	1.323
Not-Completely-Independent ADLs	128	47	39%	34%	0.285	1.145
PMH CVA	37	15	11%	11%	0.875	0.025
CRI/ ESRD	71	29	22%	21%	0.846	0.038
Angina Pectoris	102	36	31%	26%	0.258	1.279
CHF (III or IV)						

Recent MI	90	41	27%	29%	0.656	0.198
CVA	14	8	4%	6%	0.49	0.477
Coma	13	3	4%	2%	0.326	0.965
Ventilation	145	71	44%	51%	0.178	1.817
Hypotension	94	35	28%	25%	0.439	0.599
S3 Gallop	1	0	0%	0%	0.514	0.425
Oliguria	4	2	1%	1%	0.848	0.037
Pulmonary Edema	73	37	22%	26%	0.3.065	0.198

Sepsis	5	20	6%	8%	0.493	0.469
Pneumonia	12	34	14%	14%	0.956	0.003
Recent MI	24	66	28%	27%	0.817	0.053
CVA	1	13	1%	5%	0.104	2.649
Coma	2	11	2%	4%	0.383	0.761
Ventilation	35	110	41%	45%	0.551	0.355
Hypotension	16	78	19%	32%	0.022	5.246
S3 Gallop	0	1	0%	0%	0.555	0.348
Oliguria	0	4	0%	2%	0.236	1.405
Pulmonary Edema	19	54	22%	22%	0.952	0.004
Abnl BUN	11	37	13%	15%	0.626	0.237
Abnl Cr	34	102	40%	42%	0.792	0.069
Abnl pH	9	66	11%	27%	0.002	9.606
Abnl $PaCO_2$	24	71	28%	29%	0.896	0.017
Abnl PaO_2	2	21	2%	9%	0.052	3.764
Abnl Bicarb	3	28	4%	11%	0.031	4.626

Table 2: Univariate analysis of clinical characteristics and survival in the derivation cohort.

The four features in bold demonstrated a statistically significant difference between patients that did and did not survive (via chi-square analysis at the 0.05 level).

Description of the clinical prediction rule

We define the Dartmouth Score as the best ten-feature clinical prediction rule generated using LDA (Table 3). The rule includes both protective features and those indicative of non-survival. It achieves a specificity of 82.4% and a sensitivity of 42.7% on the validation cohort. In corim

medical phenomena makes it difficult to fully rationalize the inclusion of each clinical variable into our prediction rule. In the next few paragraphs we propose potential medical justification to support our rule's inclusion of several clinical variables. These ideas are intended to

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