

Supplemental Digital Content 1: Statistical Analysis - Internal Validation Methods

The modeling strategy was based on a univariate screening approach with subsequent backwards stepwise elimination which dropping process was based on the p -value. Terms which were not statistically significant at an α -level of 0.05 were dropped from the model. The results of the final multivariable model showed that one variable was negatively associated with a favorable functional outcome, namely, day-1 Logistic Dysfunction Organ score and two were positively associated with a favorable functional outcome, namely, ventricular fibrillation/tachycardia as first recorded rhythm and no epinephrine to treat postcardiac arrest shock

Different strategies were carried out in order to confirm our results which could be dependent to our sample.

First of all, we add to the three variables selected in this way, two additional variables, previously reported to affect outcomes, namely, occurrence during nonstandard working hours and hemorrhagic shock, which were forced into the final model. Using this process, our final results were therefore not only a data-driven procedure insofar as the final model also includes important already known predictors which were not found with our data.

Then, we performed several sensitivity procedures to validate our results, at least from internal point of view.

We performed a forward selection model. In this approach, the initial model involves only an intercept, and additional covariates are added one by one. Having effected this strategy, we obtained exactly the same selected model with three variables selected: Logistic Dysfunction Organ score, ventricular fibrillation/tachycardia as first recorded rhythm, no epinephrine to treat postcardiac arrest shock.

Secondly, we performed an internal validation of the selection process using a bootstrap procedure. In that approach we created by bootstrap $n = 1,000$ new datasets. Within each dataset we carried out a backward stepwise procedure. Then, we estimated percentages of selections of each variable. The variables kept in our initial model were the most three selected variables: Logistic organ

Dysfunction score was selected in 80.1% of the procedures, fibrillation/tachycardia as first recorded rhythm in 30.2% and epinephrine to treat postcardiac arrest shock in 29.3% of the procedures.¹

Finally, we used a Lasso procedure to overcome the potential overparameterized issue of our multivariate model. The use of a penalized likelihood allows to determine which covariates have a nonnull coefficient given the value of the parameter of the penalty (usually noted lambda).² We fixed lambda to obtain six nonnull coefficients (including the intercept). Then we obtained a model validating a rule of thumb of 1 covariate per 10 events. Those nonnull coefficients corresponded to the following covariates: Logistic Dysfunction Organ score at intensive care unit admission, time from collapse to return of spontaneous circulation (no flow + low flow), ventricular fibrillation/tachycardia as first recorded rhythm, Simplified Acute Physiology Score version II score at intensive care unit admission, epinephrine after resuscitation. Then we performed a backward selection from a model being composed of these five variables that selected the same three variables: Logistic Dysfunction Organ score ($p < 0.0001$), ventricular fibrillation/tachycardia as first recorded rhythm ($p = 0.0206$), no epinephrine to treat postcardiac arrest shock ($p = 0.0174$).

All these additional sensitivity analyses are consistent with our final results, which seem therefore robust from a selection process point of view. Nevertheless, our results should be replicated to valid the measured impact of the selected variables.

References

1. Harrell FE: Regression Modeling Strategies. Springer-Verlag: New York, 2001
2. Tibshirani R: Regression shrinkage and selection *via* the lasso. J R Stat Soc Series B Stat Methodol 1996; 58:267-88