



Decompensated heart failure patients: there are simple parameters that could be integrated in a machine learning process to improve our strategies

Erwan Donal

Cardiologie & CIC-IT 1414, CHU RENNES, LTSI INSERM U1099, Université Rennes-1, Rennes, France

Correspondence to: Erwan Donal, MD, PhD. Cardiologie, CHU Rennes, CIC-IT 804, LTSI INSERM 1099, Université Rennes 1 Hôpital Pontchaillou, rue Henri Le Guillou 35000, Rennes, France. Email: erwan.donal@chu-rennes.fr.

Comment on: Voors AA, Ouwerkerk W, Zannad F, *et al.* Development and validation of multivariable models to predict mortality and hospitalization in patients with heart failure. *Eur J Heart Fail* 2017. [Epub ahead of print].

Received: 09 April 2017; Accepted: 30 April 2017; Published: 14 June 2017.

doi: 10.21037/jlpm.2017.05.01

View this article at: <http://dx.doi.org/10.21037/jlpm.2017.05.01>

Heart failure (HF) remains an extremely severe disease despite pharmacological innovation (1) as well as devices that are largely used. Still HF is a diagnosis associated with a mortality greater than most cancers (2). A large effort is thus, still, required to define best the strategies and the individualized managements that are supposed to improve the prognostic of the disease for any single patient with his co-morbidities and specificities. Voors *et al.* published a very impressive work based on the BIOSTAT-CHF research program (3). BIOSTAT-CHF is a large European project that was specifically designed to develop and validate risk prediction models in patients with HF. The work is European large work with a derivation and validation cohorts. At the reading, this paper is highly supposed to be representative of what is found in most of our centers across Europe. Therefore, this paper is extremely important to consider and perhaps to integrate in a scoring system as we have and as we are using in many clinical situation like the atrial fibrillation or the pulmonary embolism (4,5).

The five strongest predictors of mortality were more advanced age, higher blood urea nitrogen and N-terminal pro-B-type natriuretic peptide, lower haemoglobin, and failure to prescribe a beta-blocker. The five strongest predictors of hospitalization owing to HF were more advanced age, previous hospitalization owing to HF, presence of oedema, lower systolic blood pressure and lower estimated glomerular filtration rate.

These are simple parameters that could be computed

and perhaps be used for best managing the indication of a hospitalization stay and best managing the intensity of the medical treatment and of the post-hospitalization follow-up.

Tele-medicine is coming from everywhere as well as big data (6). The parameters proposed by Voors *et al.* can easily be obtained in most patients and then be integrated in large predicting risk models that could help or guide non-expert physician to decide for a more or less specialized medical intervention of any single HF patient.

The risk stratification of HF patients could improve clinical outcome and cost-effectiveness of our practices. But, many clinical scores have been proposed based on in-hospital and post-discharge cohorts. Most models show a good capacity to discriminate patients who reach major clinical end-points, with C-indices generally higher than 0.70, but their applicability in real world populations has been non-extensively evaluated (3,7-9). The use of risk score-based stratification might improve patient outcome but are not underscored like others in current HF guidelines (1). Variables proposed in Voors *et al.* paper are recurrent in most scores and should always be considered when evaluating the risk of an individual patient hospitalized for acute HF. The remaining work is even more important that the new treatment strategies and agents have not been tested for their impact on the predictive risk of death according to scores. That could be something to look for and the question then would be really to implement them in our reasoning in front of any single patient as we do with other scores. That has to be

tested and we shouldn't limit our effort in computing large databases for getting risk factors that are rather intuitive and known.

Nevertheless, it is highly probable that this scoring approach will have a limited impact on the quality of care as the relevance of scores will probably be equivalent to the relevance of the scores that we are using when deciding for surgery or TAVI (10). We integrate the scores in our multivariable decision making process. But the final decision is frequently in inadequation with the score because the statistical risk assessment cannot replace the clinical expertise and the information obtained from the complexity of the whole history of any single patient.

So, risk factors and risk prediction tools have to be implemented in our daily clinical practice but not for their own. The algorithms, the big data approaches should be used to not underestimate the risk for any single patient hospitalized everywhere. It will probably not affect the prognosis of patients hospitalized in highly specialized unit but it will mainly affect the one of patients hospitalized in non-cardiological units or primary care hospitals. So according to the scores and big data approach, patients could be re-oriented to specialized centers or physicians. Then, prognostic factors like to ones highlighted by Voors *et al.* should not be used alone (3). They should help for selecting patients that require a heart team multidisciplinary expertise for finalizing the decision making process.

Scores for the risk stratification of HF patients are useful tools that might support, not replace, clinical judgment and supply a rational approach for prognostication of the individual patient. Further prospective studies are necessary to evaluate if the outcome of HF patients can be improved with the use of these tools and their implementation in new treatments or monitoring strategies.

Acknowledgments

Funding: None.

Footnote

Provenance and Peer Review: This article was commissioned and reviewed by Executive Editor Zhi-De Hu (Department of Laboratory Medicine, General Hospital of Ji'nan Military Region, Ji'nan, China).

Conflicts of Interest: The author has completed the ICMJE

uniform disclosure form (available at <http://dx.doi.org/10.21037/jlpm.2017.05.01>). The author has no conflicts of interest to declare.

Ethical Statement: The author is accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Open Access Statement: This is an Open Access article distributed in accordance with the Creative Commons Attribution-NonCommercial-NoDerivs 4.0 International License (CC BY-NC-ND 4.0), which permits the non-commercial replication and distribution of the article with the strict proviso that no changes or edits are made and the original work is properly cited (including links to both the formal publication through the relevant DOI and the license). See: <https://creativecommons.org/licenses/by-nc-nd/4.0/>.

References

1. Ponikowski P, Voors AA, Anker SD, et al. 2016 ESC Guidelines for the diagnosis and treatment of acute and chronic heart failure: The Task Force for the diagnosis and treatment of acute and chronic heart failure of the European Society of Cardiology (ESC) Developed with the special contribution of the Heart Failure Association (HFA) of the ESC. *Eur Heart J* 2016;37:2129-200.
2. Ho KK, Pinsky JL, Kannel WB, et al. The epidemiology of heart failure: the Framingham Study. *J Am Coll Cardiol* 1993;22:6A-13A.
3. Voors AA, Ouwkerk W, Zannad F, et al. Development and validation of multivariable models to predict mortality and hospitalization in patients with heart failure. *Eur J Heart Fail* 2017. [Epub ahead of print].
4. Kirchhof P, Benussi S, Kotecha D, et al. 2016 ESC Guidelines for the management of atrial fibrillation developed in collaboration with EACTS. *Eur Heart J* 2016;37:2893-962.
5. Konstantinides SV, Torbicki A, Agnelli G, et al. 2014 ESC guidelines on the diagnosis and management of acute pulmonary embolism. *Eur Heart J* 2014;35:3033-69, 3069a-k.
6. Schoenhagen P, Mehta N. Big data, smart computer systems, and doctor-patient relationship. *Eur Heart J* 2017;38:508-10.
7. Fonarow GC, Abraham WT, Albert NM, et al. Association between performance measures and clinical outcomes for patients hospitalized with heart failure. *JAMA* 2007;297:61-70.

8. Metra M, Mentz RJ, Chiswell K, et al. Acute heart failure in elderly patients: worse outcomes and differential utility of standard prognostic variables. Insights from the PROTECT trial. *Eur J Heart Fail* 2015;17:109-18.
9. O'Connor CM, Mentz RJ, Cotter G, et al. The PROTECT in-hospital risk model: 7-day outcome in patients hospitalized with acute heart failure and renal dysfunction. *Eur J Heart Fail* 2012;14:605-12.
10. Osswald BR, Gegouskov V, Badowski-Zyla D, et al. Overestimation of aortic valve replacement risk by EuroSCORE: implications for percutaneous valve replacement. *Eur Heart J* 2009;30:74-80.

doi: 10.21037/jlpm.2017.05.01

Cite this article as: Donal E. Decompensated heart failure patients: there are simple parameters that could be integrated in a machine learning process to improve our strategies. *J Lab Precis Med* 2017;2:27.