Development of a machine-learning tool to risk stratify emergency department patients with acute heart failure

Dana R Sax, MD MPH, Mare E Reed, DrPH, Oleg Sofyrgin PhD, David R Vinson, MD, Dustin W Ballard, MD MBE, Mamata Kene, MD MPH, and Jamal S Rana, MD PhD

|  |  |
| --- | --- |
| Challenge | **No acute heart failure (AHF) risk stratification tool is currently available for bedside use. Over 80% of AHF patients are admitted to the hospital across the U.S., and there is widespread variation in admission and adverse event rates, highlighting an opportunity to improve AHF risk prediction.** |
| Existing Evidence | There have been several recently proposed risk prediction rules for AHF, although they have not yet been validated in the U.S. population and are not ready for bedside use. We used two of these externally developed rules as a basis for developing a KPNC-specific risk tool using additional variables and machine-learning methods. |
| Target Population | KPNC adult members presenting to an emergency department with symptoms of AHF. |
| Intervention or Exposure | Using a retrospective cohort of 26,000 ED patients with AHF, we assessed 70+ clinical variables and their association with a 30-day serious adverse events (including death, CPR, intra-aorta balloon pump, endotracheal intubation, renal failure requiring dialysis, myocardial infarction, or coronary revascularization). |
| **Outcomes/Key Findings** | **We developed a highly accurate ED-based AHF risk prediction tool, and as far as we know, the first ED AHF model that uses machine learning approaches.** The overall 30-day serious adverse event rate was 18.8%. There was significant mismatch between predicted risk and admission decision (many low-risk patients were admitted and many high-risk patients were discharged). We assessed model performance to accurately predict an adverse outcome and compared logistic regression and four machine learning models. The base logistic regression model had an area under the curve of 0.76 (95% CI 0.74-0.77); use of additional variables and an XGboost machine learning model increased the area under the curve to 0.85 (95% CI 0.83-0.86). |
| **Resulting Action/Change** | **We are now working to build this machine-learning risk prediction tool for real-time, bedside use, and pilot test it at three EDs for feasibility and safety testing.** |
| Additional Recommendations | Pending a tool that is ready for widespread use, dissemination of information to date from the study may inform clinicians on the general question of targeting admission to risk and patterns for under and over-treatment in this complex population to optimize resource use and improve patient safety. |
| Implementation Tools | We will work on implementation in the next phase (currently funded) of the project. |
| Implementation Measurement | N/A |
| Reference | Accepted for publication at Annals of Emergency Medicine 9/2020: “Sax DR, Mark DG, Huang J, Sofrygin OX, Rana JS, Collins SP, Storrow AB, Liu D, Reed ME. Use of machine learning to develop a risk stratification tool for emergency department patients with acute heart failure. *Ann Emerg Med*. 2020 Dec [Epub ahead of pring]. |