

Electronic frailty index for predicting mortality outcome of patients undergoing trans-aortic valvular implantation

Chen Y.¹; Zhou J.²; Lee S.³; Liu T.⁴; Wu W.⁵; Hothi S.⁶; Zhang Q.²; Tse G.⁴; Wang Y.⁷

¹University College London, School of Pharmacy, London, United Kingdom of Great Britain & Northern Ireland

²City University of Hong Kong, School of Data Science, Hong Kong, China

³Hong Kong Li Kai Shing Institute of Health Sciences, Laboratory of Cardiovascular Physiology, Hong Kong, China

⁴2nd Hospital of Tianjin Medical University, Department of Cardiology, Tianjin, China

⁵Hong Kong Li Kai Shing Institute of Health Sciences, Hong Kong, China

⁶The University of Hong Kong, Department of Pharmacology and Pharmacy, Hong Kong, Hong Kong

⁷Xiamen University, Xiamen Cardiovascular Hospital, Xiamen, China

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Objective: Electronic frailty index for predicting mortality outcome of patients undergoing transaortic valvular implantation (TAVI) served as useful surrogates but is associated with a poor prognosis since it needs long time to determine the frailty status and develop the index based on electronic health records. We identify significant risk mortality predictors and tested the hypothesis that an electronic frailty index incorporating ECG measurements and laboratory examinations using a machine learning survival analysis approach can improve TAVI mortality prediction.

Design: A territory-wide observational study which involved a total of 450 patients (49.11% females, 22 mortalities) diagnosed undergoing TAVI and admitted to public hospitals from Hong Kong.

Methods: Demographics (TAVI presentation age, gender, severity of TR, AR, MR, PR, INR of TAVI presentation), prior comorbidities before TAVI presentation, ECG measurements, and CBC and LRFT laboratory examinations were analyzed. Cox regression and a supervised sequential ensemble learning algorithm: gradient boosting survival tree (GBST) model, was applied to predict mortality. Significant univariate and multivariate risk predictors of mortality were identified. Importance ranking of variables were obtained with GBST model and used to build the frailty models. Comparisons were provided with baseline models of random survival forests and multivariate Cox regression.

Results: The median TAVI presentation age was 82.3 years (83.8 years in mortalities, and 82.1 years in alive patients). INR of TAVI presentation in mortalities (median: 1.32) is much higher than alive ones (median: 1.07). Severe TR (hazard ratio, HR: 8.93, 95% CI: [3.22, 24.78], p value < 0.0001), INR of TAVI presentation (HR: 2.74, 95% CI: [1.84, 4.09], p value < 0.0001), cumulative hospital stays (HR: 1.01, 95% CI: [1.00, 1.01], p value = 0.0008), aspartate transaminase (HR: 1.01, 95% CI: [0.98, 1.002], p value = 0.0002), and bilirubin (HR: 1.02, 95% CI: [1.01, 1.02], p value = 0.0003) are significant mortality risk predictors. Machine learning survival analysis model found that APTT demonstrates the most important strength, followed by INR of TAVI presentation, severe TR status, cumulative hospital stays, cumulative readmission times, creatinine test, urate test ALP test, and ECG measurements of QTc and QT. GBST significantly outperformed random survival forests and multivariate Cox regression (precision: 0.91, recall: 0.89, AUC: 0.93, C-index: 0.96, and KS-index: 0.50) for mortality prediction.

Conclusions: Electronic frailty index based on demographics, prior comorbidities, hospitalization characteristics, ECG measurements, and laboratory examinations can efficiently predict mortality outcome of patients undergoing TAVI. Machine learning survival learning model significantly improves the risk prediction performance and improves the construction of the frailty models for tailored interventions of TAVI patients in clinical practices.